OPTIMIZATION OF STIFFENED VARIABLE ANGLE TOW PANELS CONSIDERING THE POST-BUCKLING BEHAVIOR

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ABSTRACT

This study proposes a new method for optimizing steering layup path of a stiffened CFRP panel. Bezier curve was applied to determine the steering orientation of a skin panel. The objective functions were set to maximize the first buckling load and ultimate failure load (collapse load or initial fiber failure load) under compressive loading. The variables for the optimization were control points of Bezier curve. Artificial Neural Network (ANN) and Genetic Algorithm (NSGA-II) were applied to the optimization procedure. The results demonstrated that the stiffened panels optimized using Bezier steering layup path and proposed optimization procedure have superior structural performance compared to the initially designed panel.

1 INTRODUCTION

Carbon fiber reinforced plastic (CFRP) composites are widely applied to primary aircraft structures. Composite stiffened panels are applied to aircraft wings and fuselages because they can transfer loads much more efficiently than unstiffened panels. To achieve the required buckling load while reducing structural weight, geometrical dimensions and stacking sequence were optimized [1, 2]. In aircraft design, fuselage section is designed to work in the post-buckling regime. Panels can transfer load up to collapse load after buckling. Since the post-buckling analysis is computationally expensive, Irisarri *et al*. performed stacking sequence optimization using a combination of an approximation of the objective function by Radial Basis Functions and optimization algorithm [3].

Recent advancements of manufacturing techniques represented by the Automated fiber placement (AFP) has led to the possibility of having steering layup laminates where the fiber orientation can change over the plane of a ply. Further structural weight reduction may be achieved by applying the fiber orientation of optimal curved path for the geometry and load conditions.

A concept called variable stiffness panel (VSP), which determines the layup path with two angular variables, improves mechanical properties because the stiffness such as Young's modulus and shear modulus are optimally displaced locally within each layer [4]. Although there are many previous studies on the application of VSP to plates, few studies have applied it to stiffened panels. Coburn *et al*. applied VSP to stiffened panel and reported improved buckling load [5]. Furthermore, two previous studies optimized the layup path to maximize the buckling load [6, 7]. However, the compatibility of improved buckling load and failure load after buckling has not been examined.

In this study, steering layup was applied to stiffened panels, and optimization of the layup path was performed focusing on initial buckling and post-buckling behavior under compressive loading. Steering layup using Bezier curves as an indicator was introduced in the 0° layer of the skin plate for stiffened panel. Subsequently, analytical optimization was performed focusing on the initial buckling load and failure load after buckling. It was performed by a combination of the approximation of the objective function by Artificial Neural Network (ANN) and a multi-objective optimization algorithm, NSGA-II.

2 STIFFENED PANEL NOMINAL DESIGN AND FINIT ELEMENT MODELING

Specimen geometry (Fig. 1), which was tested under compressive load in a previous study [8], was taken here as the initial design for the optimization. First, the FEM analysis results of initial design were compared with the experimental results. The specimen consists of a 538 × 728 mm skin plate and four blade stiffeners. The material was carbon/epoxy T800/924C [8] and the stacking sequence were $[90/0_2/90/\pm45/0/90/\pm45/0]_s$ for the skin plate and $[90/0/90/0/\pm45/90/0_2/90/\pm45/\pm45/90]_s$ for the web of the stiffener. A FE model of the panel was performed using a commercial FEM software ABAQUS Standard 2017. The panel was meshed with shell element S4R (56,784 elements).

The buckling load was estimated by buckling eigenvalue analysis with a reference load of 1 N .

$$P_{\mathrm{cr}} = P_0 + \lambda_{\mathrm{i}} P. \tag{1}$$

Where P_{cr} is buckling load, P_0 is initial load, P is reference load, and λ_{i} is eigenvalue, respectively. The initial buckling load was calculated to be 117.6 kN (experiment+6.9%). It is accurately estimated and predicted buckling mode is good agreement with the previous research [8]. After that, post-buckling analysis was performed with initial geometrical imperfection based on the results of the eigenvalue analysis. The first buckling mode was used to impose the out-of-plane geometric imperfections in the panel model with maximum amplitude of 5.0 % of the skin thickness. This imperfection was determined by sensitivity study of several mode combinations and magnitudes. In post-buckling analysis, if stiffness is lost due to snap-through buckling, analysis may not be able to continue using Newton-Raphson techniques. Several methods have been proposed to stabilize the analysis. In this study, we used pseudo-damping [9], which is highly robust for optimization. Global equilibrium equations applying pseudo-damping given by [10],

$$\boldsymbol{F}_{\mathrm{ext}} - \boldsymbol{F}_{\mathrm{int}} - c\boldsymbol{M}\frac{\Delta \boldsymbol{u}}{\Delta t} = 0. \tag{2}$$

Where $\boldsymbol{F}_{\mathrm{ext}}$ is external force vector, $\boldsymbol{F}_{\mathrm{int}}$ is internal force vector, c is damping factor, $\boldsymbol{M}$ is an artificial mass matrix calculated with unit density, and $\Delta\boldsymbol{u}$ is the displacement increment vector. The damping factor c was determined by sensitivity analysis focusing on convergence and dissipated energy. We confirmed that collapse load was same with the analysis using the Riks method. As a result, Fig.2 shows the load-displacement curve and comparison of out-of-plane displacement with experiment at mode switch point and after collapse. The deformation behavior of the experiment could be represented in this analysis. Collapse load was 699.6 kN (experiment +16%). Simulating material failure and delamination between the skin and stiffeners increased the accuracy, but these were not considered in this study to reduce computation time for optimization.

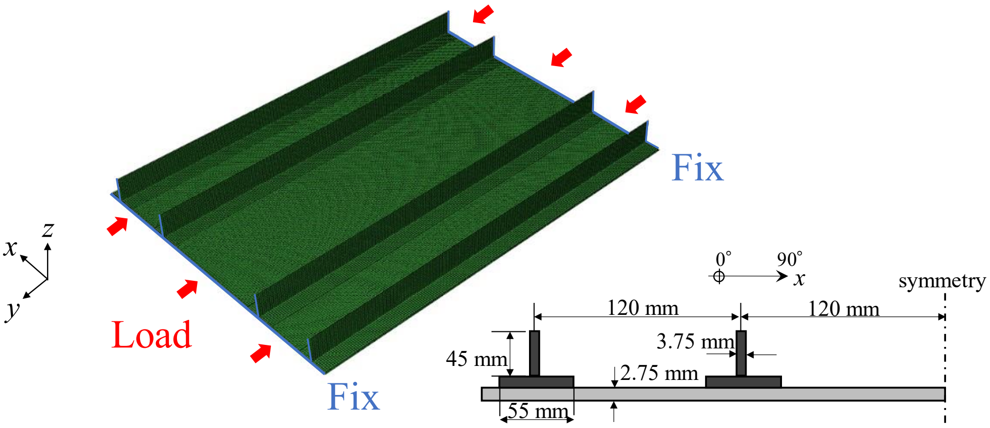


Figure 1: Model of blade-stiffened panel [8] and boundary condition.

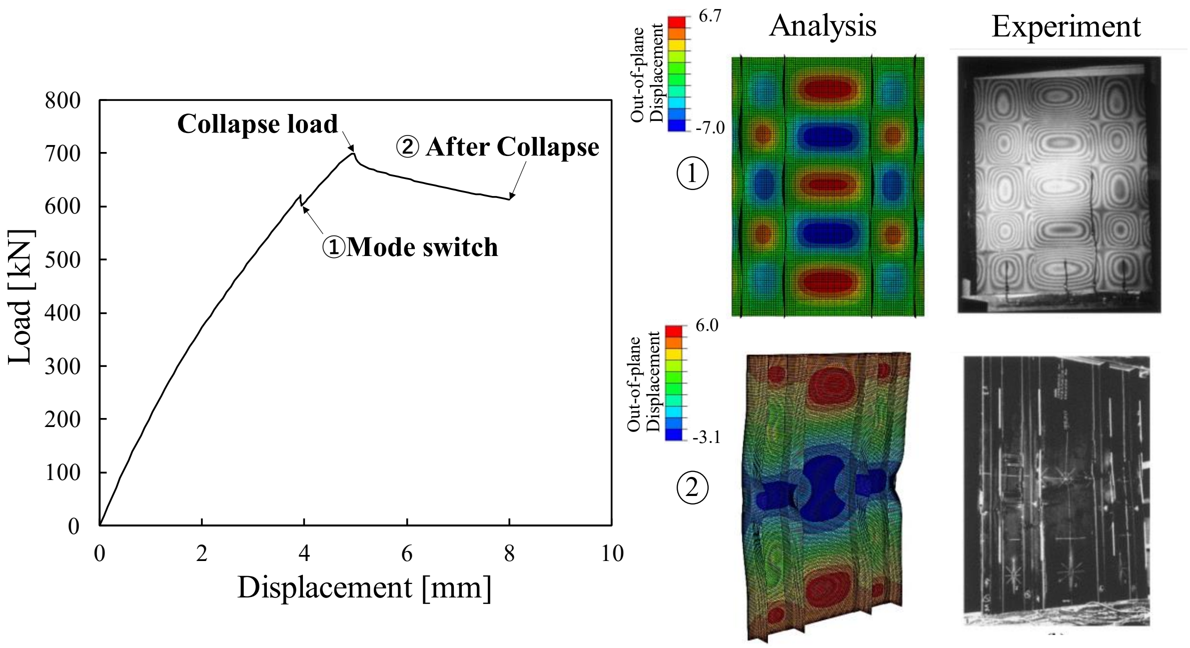


Figure 2: Results of a post-buckling analysis. Experimental results are cited from Ref. [8] (Panel2).

3 LAYUP PATH CONFIGURATION

In this paper, Bezier curve was used to represent the fiber paths. It is N-1 order functions defined by N control points. This curve is easy to handle as a path indicator because it is encapsulated in control points. Assuming that the control points are B_0, B_1,...B_{N-1}, a Bezier curve is expressed as Equation (3). where t varies from 0 to 1. $J_{n,i}$(t) is the Bernstein basis polynomials.

$$\mathrm{P}(t) = \sum_{i=0}^{N-1} B_i\, J_{N-1,i}(t). \tag{3}$$

Five control points are used in Fig. 3. Point B_1 moves on $y = \mathrm{h_{skin}}/2$, and point B_2 can move freely in the first quadrant. Point B_3 is fixed at the origin. Points B_4, B_5 are arranged symmetrically with B_2, B_1 respect to the origin. Then, the variables are the x-coordinate $B_1(x)$, $B_2(x)$ and the y-coordinates B_2(y). Furthermore, by normalizing as follows, the layup path is determined by the three variables α, β, and γ.

$$\alpha = B_1(x)/(\mathrm{w_{skin}}/2), \quad \beta = B_2(x)/(\mathrm{w_{skin}}/2),$$
$$\gamma = B_2(y)/(\mathrm{h_{skin}}/2) \quad (0 \le \alpha, \beta, \gamma \le 1)$$

In the FEM analysis, steering layup was introduced by rotating the material coordinate system of each element using user subroutine ORIENT.

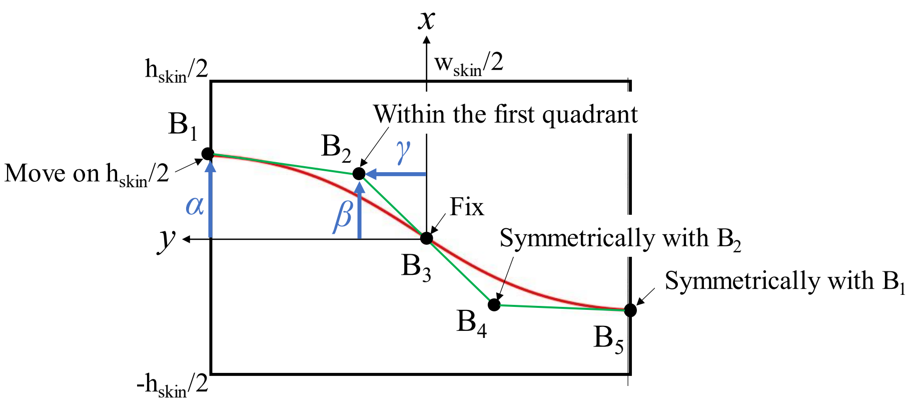


Figure 3: Definition of steering layup path using Bezier curve.

4 OPTIMIZATION METHODOLOGY

Genetic Algorithm (GA) was used for optimization of layup paths. GA is a metaheuristic approach inspired by the process of natural selection. GA performs optimization using variables as chromosome and updating generations while applying Genetic operation (Selection, Crossover and Mutation). FEM analyses were used for evaluation during optimization. In this study, these are replaced by interpolating surrogate model, which approximate the objective functions, in order to reduce the calculation costs during the optimization process. We introduced Artificial Neural Network (ANN) as a surrogate model. Fig.4 shows the flowchart of optimization process.

First, a combination of design variables was determined by the Latin Hypercube sampling (LHS) [11] and FEM analyses were performed with each selected design variables. Bezier curve variables were α, β and γ which determine the layup path. LHS is a statistical method for generating a near random sample of parameter values from a multidimensional distribution. We created 950 combinations of 3 variables using LHS. The geometry of the skin and stringers was the same as the initial panel, and the analyses were performed for 950 times by changing the layup path. These analyses were performed automatically be making a python program. At first, linear eigenvalue analysis was performed. Then, python program rewrites the part of the input-file related to the initial imperfection to introduce initial imperfection for post-buckling analysis. After that, nonlinear post-buckling analysis was performed. If the reaction force was less than the specified value after the collapse load, each analysis was terminated by user subroutine URDFIL.

Second, we performed supervised learning with ANN using FEA results as training data. ANN consists of input layer, hidden layer (6 layers), and output layer. When variables (α, β, and γ) are entered in the input-layer, the buckling load N_{cr}, and failure load $N_{failure}$ are output. Stochastic Gradient Descent (SGD) was used as the learning algorithm. To reduce learning time, Back-propagation was used. Learning accuracy was verified by separating teacher data and test data.

Finally, optimization was performed using Non-dominated Sorting Genetic Algorithm (NSGA-II) [12]. NSGA-II is a method that extends GA to multi-objective optimization. Forecasting model learned by ANN was used for evaluation doing optimization. We introduced the minimum radius of curvature r_{min} that can be produced by AFP as a constraint for optimization.

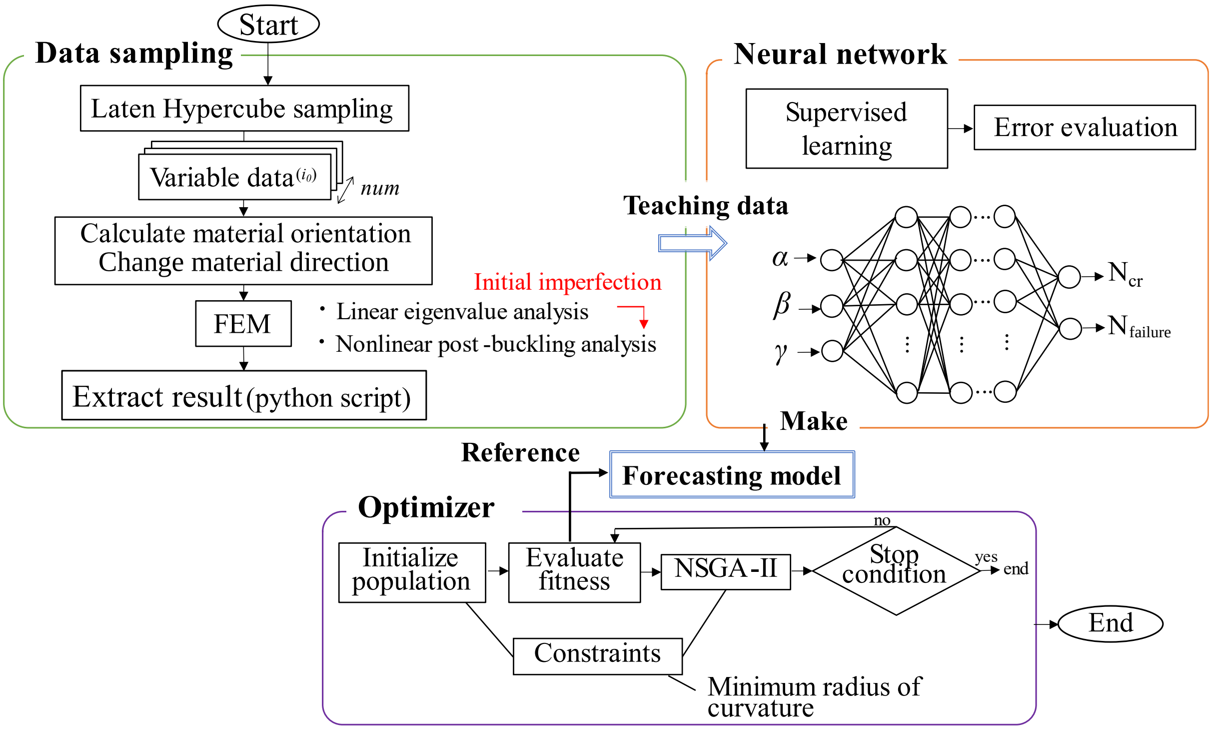


Figure 4: Flowchart of optimization.

5 OPTIMIZATION PROBLEM

The skin and stringer dimensions were fixed at the same values as the initial panel. Steering layup was introduced in the 0° layer of the skin. So that the layers were symmetrically stacking, we alternated stacking layer of steering paths with Bezier curves and its inverted layer. There were two objective functions. The first objective function (f_1) was to maximize the buckling load N_{cr} under compression load. The second objective function (f_2) was to maximize the failure load $N_{failure}$. Failure load $N_{failure}$ was defined as two patterns. The Pattern A was the collapse load $N_{collapse}$ of the load-displacement curve. The Pattern B was the smaller value of the collapse load $N_{collapse}$ and the initial fiber failure load $N_{initial}$. Initial fiber failure load was determined by the 2D Hashin criterion [13]. We introduced the minimum radius of curvature r_{min} = 635 [mm] [14] as a constraint for optimization.

・Tensile failure (σ_{11}>0) $$FF_t = \sqrt{\left(\frac{\sigma_{11}}{X_t}\right)^2 + \left(\frac{\tau_{12}}{S_{12}}\right)^2} \geq 1, \tag{4}$$

・Compression failure (σ_{11}<0) $$FF_c = \sqrt{\left(\frac{\sigma_{11}}{X_c}\right)^2} \geq 1. \tag{5}$$

Where FF_t and FF_c respectively stand for the evaluation values of the initiation of fiber failure under tensile and compressive loading, X_t and X_c respectively represent the tensile and compressive strength in the longitudinal direction and S_{12} denote the shear strength.

The optimization problem is as follows.

Variables: α , β , γ (Steering layup path),

Objective function: **maximize** $N_{cr,}$
maximize Pattern A: $N_{collapse}$,
Pattern B: min ($N_{collapse}$, $N_{initial}$), (6)

Constraint: radius of curvature $r > r_{min.}$

6 RESULTS

6.1 FEM ANALYSIS (DATA SAMPLING)

We performed buckling eigenvalue analysis and post-buckling analysis of 950 patterns as training data. Checking the load-displacement curve, the nonlinear behavior and collapse load $N_{collapse}$ significantly depend on the steering layup path. After that, the initial fiber failure loads were calculated by Hashin criterion. Note that the increment size during the FEA was set sufficiently small.

Fig.5 shows a correlation diagram for each pair of variables and analysis results. For initial fiber failure load $N_{initial}$, the value=0 is indicated this model did not occur fiber failure up to the collapse load. By using LHS, each set of variables can be created without bias. There is not obvious correlation between buckling load N_{cr} and failure load $N_{failure}$ ($N_{collapse}$ or $N_{initial}$). Objective function varies depending on the steering layup path, so there is a need to optimize variables.

6.2 SUPERVISED LEARNING

We performed supervised learning with ANN using analysis results. All data were divided 8:2 into teacher and test data for error evaluation. Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) were used as error indicators. In Pattern A, R^2 are (N_{cr}, $N_{failure}$) = (0.97, 0.96), RMSE are (N_{cr}, $N_{failure}$) = (1.85, 9.52). In Pattern B, R^2 are (N_{cr}, $\underline{N}_{failure}$) = (0.97, 0.9), RMSE are (N_{cr}, $N_{failure}$) = (1.86, 11.6). These values indicate that ANN model learned well.

Fig.6 shows the comparison of predicted values with FEM results using all data as training data. A relatively good agreement is shown, but some difference is seen in failure load of pattern B. This is because the setting of objective function was complex. However, since the predicted values are not dispersed and only low absolute values are predicted, this ANN model can be used for optimization.

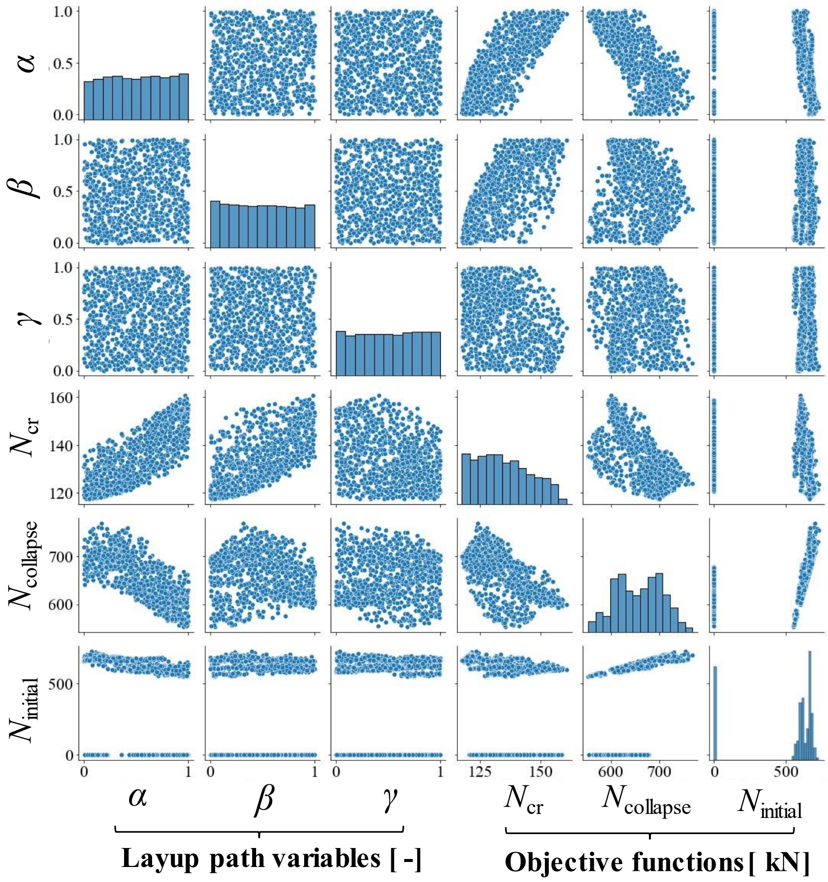


Figure 5: Correlation diagram for each pair of variables and objective functions ($N_{initial}$ = 0 indicate that fiber damage did not occur by $N_{collapse}$)

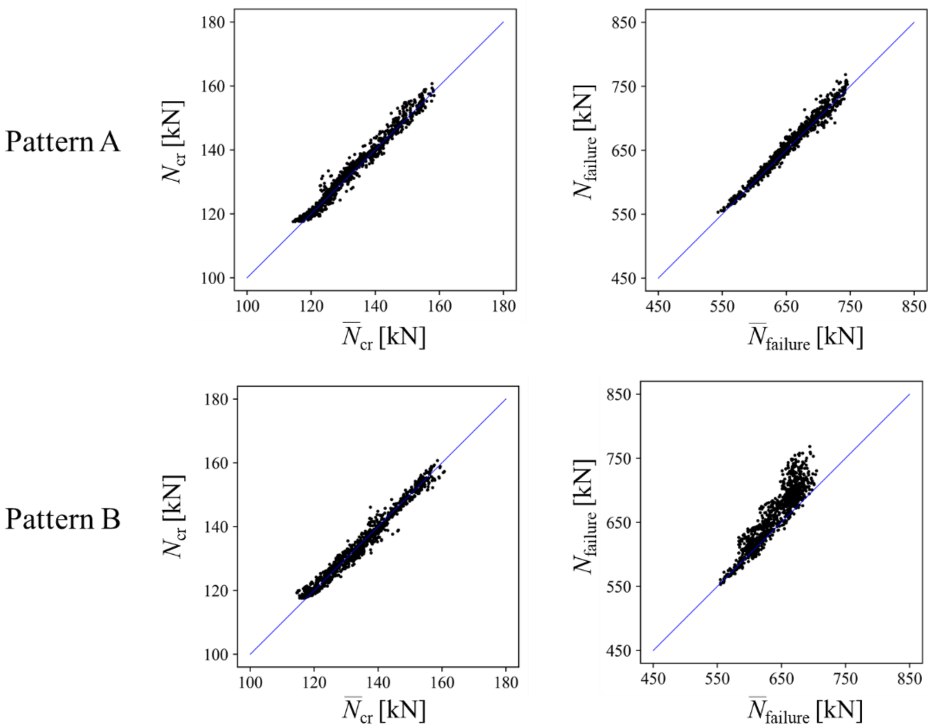
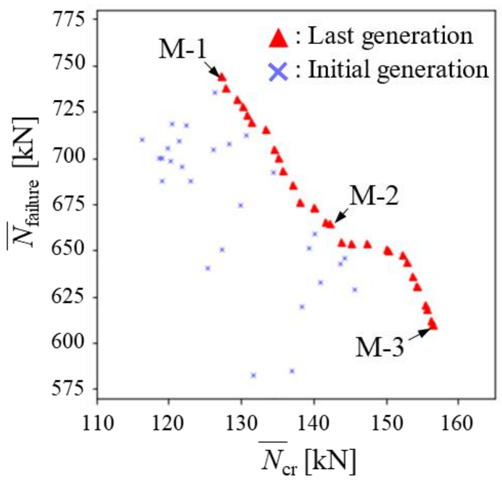


Figure 6: Comparison of predicted values with FEA results (Overline indicate predicted value)

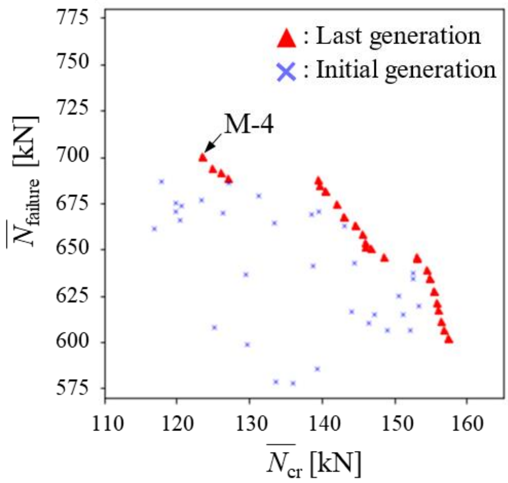
6.3 LAYUP PATH OPTIMIZATION

For optimization, the python library DEAP [15] was used as a frame work. Fig.7(a)(b) shows the multi-optimization results. In Pattern A, failure load is equal to the collapse load. In Pattern B, failure load is the smaller value of the collapse load and the initial fiber failure load. Blue crosses indicate initial solution groups and red triangles indicate final solution groups. Both patterns (A, B) could be optimized by NSGA-II. Panels with maximum buckling load, which is common objective function to both patterns, are very similar. In Pattern B, panel with maximum failure load has lower maximum value than Pattern A, which accounts for initial fiber failure. Four panels (M-1, M-2, M-3 and M-4) are extracted from the optimization results and steering layup paths are shown in Fig.7(c). Red and blue line shows the reference paths assuming 32 rows of prepreg tape with a tape width of 3.175mm stacked. There is a tendency for the steering layup path to sleep from high collapse load (M-1) to high buckling load (M-3). Comparing M-1 and M-4, M-4 was slightly closer to unidirectional stacking for 0 degree.

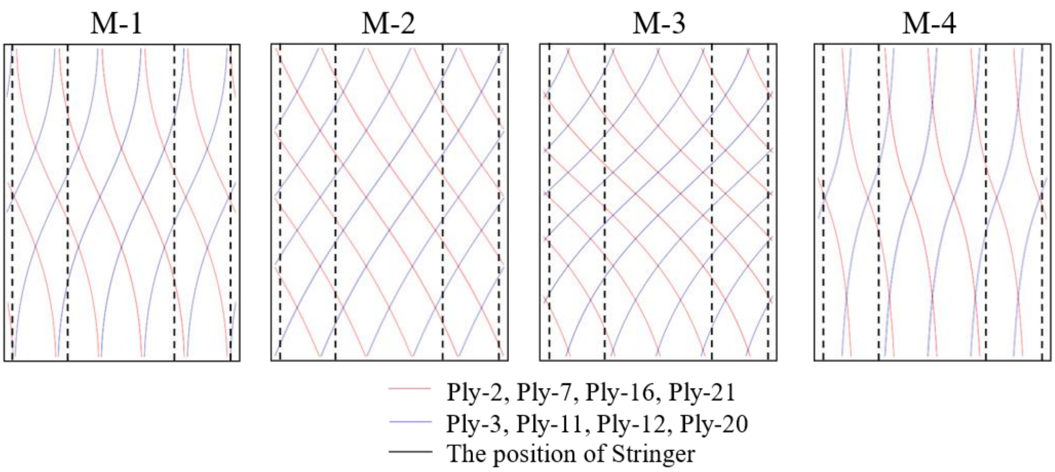
Since optimization was performed using surrogate model with ANN, extracted models (M-1, M-2, M-3 and M-4) were again analyzed by FEA to obtain accurate values. The analysis results are shown in Table1. The error between the predicted values of ANN and the FEA results is up to 1.3 %, which is sufficient for optimization. These models show a trade-off relationship between objective functions in re-analysis results, too. In particular, M-4 model has good performance than the initial panel for all valuated values. By applying the optimization method proposed in this research, it is possible to optimize the steering layup path considering post-buckling regime.



(a) Optimization result of Pattern A.



(b) Optimization result of Pattern B.



(c) Steering layup path of M-1, M-2, M-3 and M-4.

Figure 7: Results of multi-objective optimization.

Model	Buckling load N_{cr} [kN]		Failure load $N_{failure}$ [kN]			
			Collapse load		Initial fiber failure	
	FEM	ANN	FEM	ANN	FEM	ANN
M-1	126.8	127.2(+0.3%)	748.0	744.2(-0.5%)	666.5	
M-2	143.9	142.3(-1.1%)	673.3	664.4(-1.3%)	Does not occur	
M-3	158.3	156.4(-1.2%)	618.4	610.0(-1.3%)	614.2	
M-4	122.0	123.5(+1.2%)	725.2		709.5	700.2(-1.3%)
Initial panel	117.6		699.6		664.1	

Table 1: Re-analysis results of optimized panels.
(M-2 model did not occur fiber damage by $N_{collapse}$.
For the M-4 model, predicted value $N_{failure}$ are listed in the initial fiber failure.)

7 CONCLUSIONS

Steering layup defined by Bezier curves were applied to skin of stiffened composite panel. Bezier curves were defined in three variables for simplicity. In this study, these three variables were optimized. The proposed method, which use a combination of Artificial Neural Network (ANN) and Genetic Algorithms, improves mechanical properties such as buckling load and failure load. Designer can select a panel that satisfies the design requirements from the obtained set of solutions. Some of the solutions have superior buckling load and failure load than the initial panel. It was shown that both high buckling load and failure load at post-buckling regime can be achieved by optimizing steering layup path. In the future, we will incorporate fracture modes that have not been considered in this study (delamination, progressive damage).

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