MESO-STRUCTURE OPTIMIZATION OF NON-CRIMP FABRIC FOR RESIN TRANSFER MOLDING

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1. Intoroduction

Carbon-fiber-reinforced plastics (CFRP) have higher strength-to-weight and stiffness-to-weight ratios than conventional materials. Resin transfer molding (RTM) is a molding method used in the mass-production of CFRP parts. In RTM, a liquid resin is impregnated into a dry fiber preform that is placed in a mold.

The architecture of non-crimp fabrics (NCF) affects the manufacturing efficiency and the quality of the product in the RTM process. The optimization of the NCF architectures is required to improve the manufacturing efficiency and production quality. In a previous study, the homogenization method was used to calculate the homogenized property of the fiber material architecture[1]. However, the study was performed using multi-objective functions for optimizing the stiffness and permeability of the fiber material architecture is not only known to the authors.

In addition, setting the position of the design variables in shape optimization is an important issue. However, the criteria for setting the design variables are entrusted to the experience of the designer. Therefore, methods to determine appropriate design variables are required.

In this study, we optimized the NCF architecture to improve the stiffness and permeability. Therefore, we investigated the extraction of effective design variables.

2. Optimizations
2.1 NCF architecture optimization

We used multi-objective genetic algorithms (MOGA) as the optimization technique. The NCF model is shown in Fig. 1. In this optimization, the following design variables were selected: fiber bundle width, thickness, and interval. Using the liquid and solid phase homogenization method as the objective function, the in-plane and out-of-plane stiffness and permeability values were calculated.

The optimization results shown in Figs. 2 and 3 were found using a self-organizing map (SOM). The SOMs were made from the value of the design variables and objective function. The SOM shown in Fig. 2 (a) is similar to those shown in Fig. 3. Thus, the fiber bundle width and the objective function have a strong correlation. Further, the color is inverted in the stiffness and permeability SOMs shown in Fig. 3.
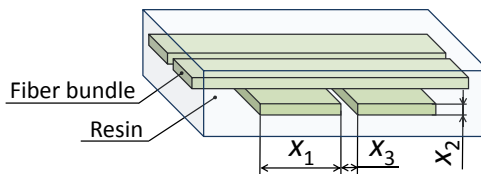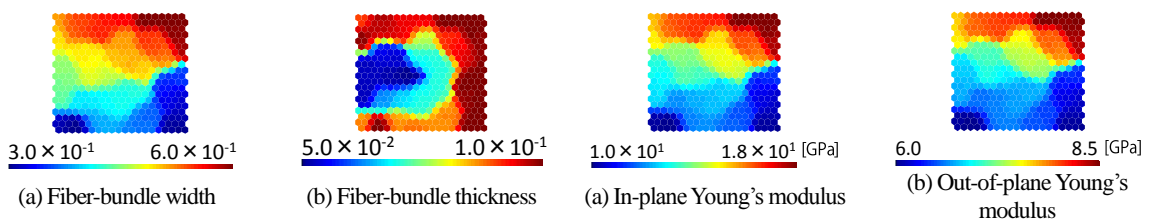

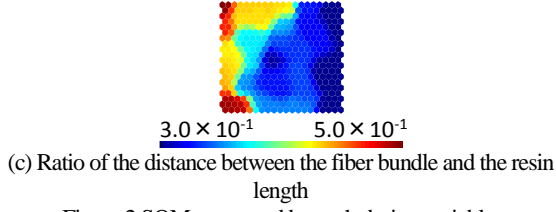Figure 1 Design variables of the NCF unit cell using an MOGA.

3.0×10^{-1}　　6.0×10^{-1}	5.0×10^{-2}　　1.0×10^{-1}
(a) Fiber-bundle width	(b) Fiber-bundle thickness

1.0×10^{1}　　1.8×10^{1} [GPa]	6.0　　8.5 [GPa]
(a) In-plane Young's modulus	(b) Out-of-plane Young's modulus

(c) Ratio of the distance between the fiber bundle and the resin length

Figure 2 SOM contoured by each design variable.

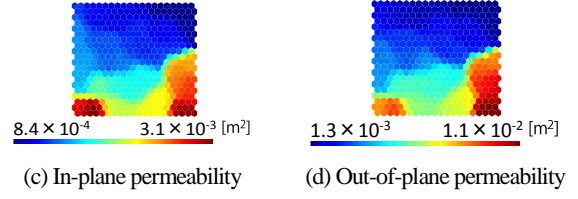(c) In-plane permeability   (d) Out-of-plane permeability

Figure 3 SOM contoured by each objective function.

2.2 Extraction of effective design variables

In this study, genetic programming (GP) was used to generate a mathematical model of the relationship between the design variables and the objective functions. Design guidelines were obtained by a mathematical formula.

The fitness fi of GP yields a reasonable prediction model using the Akaike information criterion (AIC)[2]. The AIC of the multiple regression model is given as

$$f_i = n\left(\ln\left(2\pi \frac{S_e}{n} \right) + 1 \right) + 2(m + 2) \tag{1}$$

where n is the number of samples, Se is the error sum of the squares, and m is the number of explanatory variables. The first expression on the right-hand side of Equation (1) is the error of the prediction and the second expression on the right-hand side refers to the length of the prediction model equation. The prediction model is obtained by minimizing fi. The following expressions of GP were obtained.

$$E_1 = 8.10 \times 10^2 \times x_1 \times x_2 \times (x_1 + x_2) \times (2 + x_1) + 7.50 \times 10^2 \times x_2$$
$$+ 6.81 \times 10^3 \times x_1 + 9.48 \times 10^3 \tag{2}$$

$$E_3 = 8.74 \times 10^1 \times (x_1 \times x_2 \times (x_1 \times x_2 + 2x_2)) + 3.52 \times 10^2 \times x_2$$
$$+ 2.23 \times 10^3 \times x_1 + 5.64 \times 10^3 \tag{3}$$

$$K_1 = -2.08 \times 10^{-3} \times x_1 + 2.73 \times 10^{-3} \tag{4}$$

$$K_3 = -9.35 \times 10^{-3} \times x_1 + 9.55 \times 10^{-3} \tag{5}$$

Equations (2–5) show the in-plane and out-of-plane stiffness and yield a prediction model of the in-plane and out-of-plane permeability. The x_1 coefficient, included in any prediction model, is large and this has a major impact on the objective function.

We determined the design guidelines of the obtained NCF model by increasing the constriction and waviness design variables. The optimized model simultaneously improved the elastic modulus and permeability coefficient of the trade-off relationship. The elastic modulus and permeability were improved by 4% and 20%, respectively.

3. Conclusion

The results of this study indicated that the volume of the cavity and size of the crimp affected the stiffness and permeability of the NCF. Inducing the constriction and waviness of the fiber bundles improved the performance of the NCF. The model, including constriction and waviness, was optimized again to ensure its utility as a design guideline. The optimized model simultaneously improved the converse relationship between the elastic modulus and the permeability coefficient. This confirmed the effectiveness of our method.

References

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