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Piecewise Integrated Composite Bumper Beam Design Method with Machine Learning Technique

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Abstract

In this study, the Piecewise Integrated Composite (PIC) design method with machine learning that automatically assigns different stacking sequences according to loading types was applied to bumper beam. The input value and labels of the training data for applying machine learning were defined as coordinates and loading types of reference elements that are part of the total elements, respectively. In order to compare the two-dimensional (2D) and three-dimensional (3D) implementation method, which are methods of representing coordinate value, training data were generated, and machine learning models were trained with each method. The 2D implementation method divided finite element (FE) model into each face, and generating learning data and training machine learning models accordingly. The 3D implementation method involved training one machine learning model by generating training data from the entire finite element model. The hyperparameter were tuned to optimal values through the Bayesian algorithm, and the k-nearest neighbors (k-NN) classification method showed the highest prediction rate and area under the curve-receiver operation characteristic (AUC-ROC) among the tuned models. The 3D implementation method revealed higher performance than the 2D implementation method. The loading type data predicted through the machine learning model were mapped to the finite element model and comparatively verified through FE analysis. It was found that 3D implementation PIC bumper beam was superior to 2D implementation and uni-stacking sequence composite bumper.

Keywords

Machine learning
Composite materials
PIC (piecewise integrated composite)
Bumper beam

1. Introduction

Recently, the need for automotive lightweighting research has arisen due to the strengthening of carbon emission regulations and energy use to prevent global warming [1]. As a result, the automotive industry has been conducting a lot of research on improving fuel efficiency, motor systems of electric vehicles, and lightweighting and improving the strength of parts [2]. Non-ferrous metals, thermoplastics, and composites are considered to be representative of lightweight materials, and composites, in particular, are applied to a wide range of applications due to their superior specific strength and stiffness compared to conventional materials. In particular, research is being conducted to apply composite materials to various parts of automobiles. Cheon *et al.* [3] proposed a new type of hybrid composite bumper beam for passenger cars and performed finite element analysis, and Belingardi *et al.* [4] proposed an optimized cross-sectional shape for a composite bumper beam manufactured by pultrusion by numerical analysis. Kim *et al.* [5] conducted a study on an optimized automotive hybrid composite bumper beam. Although there have been various studies on composite bumper beams, it has been common to apply a single stacking angle sequence to the entire area of the bumper beam. Jeong *et al.* [6] proposed a sectional composite bumper beam by dividing the bumper beam into five equal sections, analyzing the load types of tension, compression, and shear, and arranging the stacking order of the composite materials according to the load type. They also conducted a finite element analysis and proved that the bumper beam with a stacking angle order region divided according to the load type has an increased maximum support load and energy absorption rate than the bumper beam with a single stacking angle order. However, since the load analysis was performed by dividing the area into five equal sections arbitrarily, it is necessary to optimize the area. Ham *et al.* [7] proposed a Piecewise Integrated Composite (PIC) technique to arrange the stacking angle order by dividing sections according to the type of load by applying machine learning, and proved the superiority of the PIC design technique by applying it to a simple beam. Ji *et al.* [8] conducted a study on the stiffness of PIC simple beams using three-dimensional (3D) training data for PIC robot arms and confirmed that using 3D representation of training data is competitive. However, the previous studies were applied to models with simple geometries, and complex geometries have not been studied.

In this study, the PIC technique using machine learning was applied to a vehicle front bumper beam with a more complex shape than a simple beam. To determine the competitiveness of the two-dimensional (2D) and 3D representation methods of training data in complex geometries, both methods were applied to the front bumper beam of a vehicle, and compared and verified through finite element analysis.

2. Applying machine learning to PIC design

2.1. Applying machine learning to PIC bumper beams

The PIC design technique is a method of increasing the maximum support load and energy absorption by varying the stacking angle sequence according to the load type. In order to efficiently divide the load types in the finite element (FE) model, a classification technique is used among the machine learning algorithms. Classification is a process of distinguishing the given data by label through training data, and it is a method of training with various classification algorithms and generating a machine learning model [9]. The flow chart for designing the PIC bumper beam by applying machine learning is shown in **Figure 1**. First, the preliminary finite element analysis of the Insurance Institute for Highway Safety (IIHS) bumper beam with aluminum properties was performed to obtain the stress triaxiality value, which is the raw data of the training data. The raw data is obtained from a reference element, which is a subset of all the elements. To make the raw data into training data consisting of inputs and labels, the coordinate

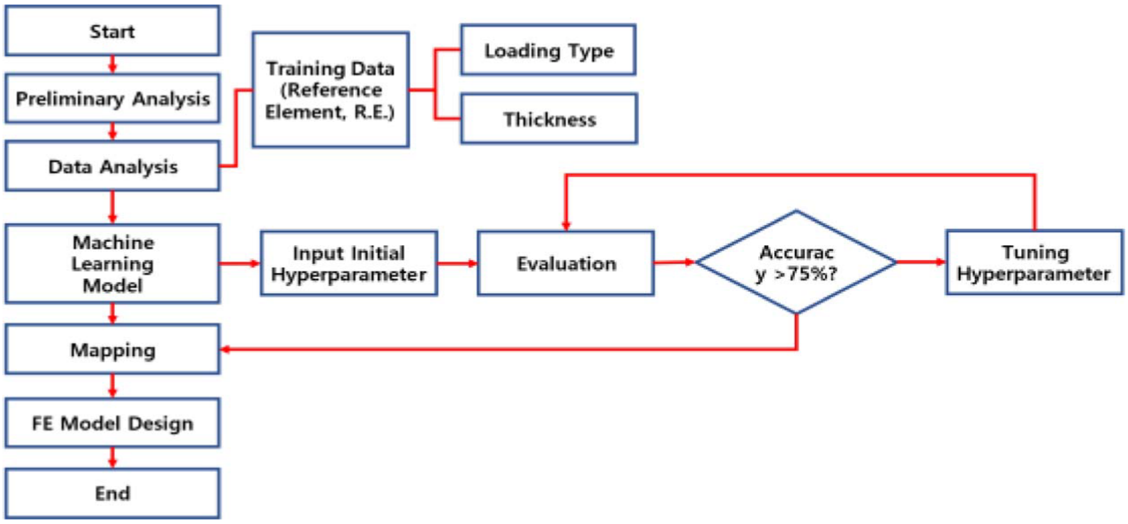

Figure 1. Flowchart of PIC design with machine learning

values of the reference element were converted into input values and the stress triaxiality property values converted into load type data [10].

In this study, machine learning algorithms include Decision tree, Support Vector Machine (SVM), and k-nearest neighbors (k-NN) algorithm. Each algorithm has its own hyperparameters, and it is known that the hyperparameters determine the performance of the model [11]. Machine learning algorithms are trained through training data to create a machine learning model, and the performance of the model can be checked through the prediction rate and the area under the curve (AUC) of the receiver operation characteristic (ROC), and if the prediction rate is less than 75%, hyperparameter tuning is performed to achieve a performance of more than 75%.

2.2. Organizing training data

In order for machine learning techniques to be applied to the PIC bumper beam design method, training data must first be generated. The training data is created based on the results obtained from the preceding finite element analysis. The preliminary finite element model is shown in **Figure 2**, which is an IIHS bumper crash analysis with a crash speed of 10 km/h. The number of elements in the bumper beam model is 19,000, and the number of reference elements is 2,400, which is about 12.7% of the

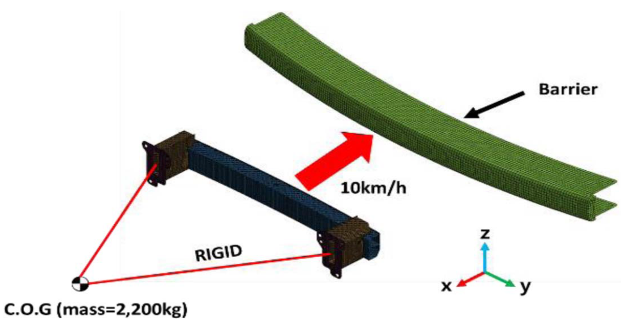

Figure 2. Preliminary FE analysis boundary condition

total elements, and the placement is regular.

In this study, the coordinate values of the reference elements are represented in 2D and 3D, and the 2D representation method divides the cross-section of the bumper beam into top face, bottom face, front face, rear face, chamfered face, and rib face, as shown in **Figure 3**, and the training data for each face is created, and the machine learning model is generated accordingly. The coordinates of the reference element, which are the input values of the training data, are in the form of (x, y), which has the advantage of showing the characteristics of the load type of each face. In the 3D representation method, the training data is generated by placing reference elements in the entire FE model without dividing the plane as in the 2D representation, and a single machine learning model is generated accordingly. The input value of the training data is represented as (x, y, z), and the advantage of using one machine learning model is that it can reduce the calculation time.

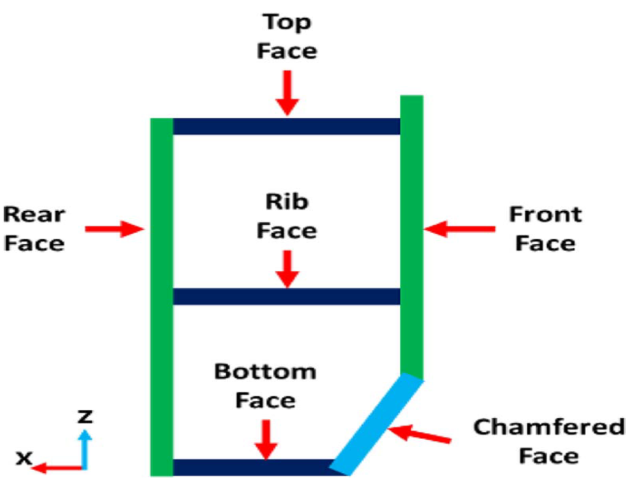

Figure 3. Cross section of bumper beam

2.3. Optimizing machine learning models and hyperparameters

In this study, Decision tree, SVM, and k-NN algorithms were used. Decision tree is a model that classifies data through the process of branching nodes with classification rules, and the hyperparameters are maximum number of splits and splits criterion [12]. SVM is a model that classifies data by determining boundaries through hyperplanes, and the hyperparameters are kernel function, kernel scale, box constraint level, and multiclass method [13]. The k-NN algorithm is a model that, when given new data, classifies it using the k training data that are closest to the data. The hyperparameters are number of neighbors, distance metric, and distance weight [14].

Each model can be tuned to achieve optimal performance through hyperparameter tuning. In this study, the hyperparameter tuning is done through Bayesian optimization algorithm. The acquisition function is expected-improvement-per-second-plus, and the number of iterations is 500 [15]. The performance metrics of the machine learning models, which were optimized through hyperparameter tuning, were compared through prediction rate and ROC-AUC. To compare the prediction rate of the 2D and 3D representation methods, the average prediction rate of the machine learning models of the 2D representation method was compared with the prediction rate of the 3D representation method. As shown in **Table 1**, the k-NN model of the 3D representation method outperformed the other models with a prediction rate of 86.3%. The ROC-AUC values of the machine learning models in the 3D representation method are shown in **Table 2**, and the ROC-AUC values also show that the k-NN classification technique has the best performance.

2.4. Results of applying machine learning

With the trained 2D and 3D representation k-NN models showing good performance, the load types were predicted for the element coordinates of the preceding finite element model, and the predicted data were mapped to the finite element model.

Figure 4 (a) and (b) are finite element models mapped with data predicted by the machine learning model trained with training data generated by the 2D and 3D representation methods, respectively. The 3D representation method, unlike the 2D representation, predicted that each face was affected by the load type of the other face in the connected part. This may be due to the fact that the 3D representation takes into account the influence of the load type on the other side due to the connectivity between each side, while the 2D representation does not.

3. Finite element analysis for PIC design validation

To verify the strength improvement of the bumper beam with the machine learning technique, the bumper beam modeled by uni-stacking sequence was compared with the bumper beam modeled by PIC. The same conditions were analyzed as in the previous finite element analysis. The material applied to the bumper beam is T700 Carbon fiber/2510 [16]. The stacking

Table 1. Machine learning model predict rate

Implementation		Prediction rate [%]		
		Decision tree	**SVM**	**k-NN**
2D	Top	75.9	79.1	80.7
	Bottom	92.1	92.5	92.5
	Front	87.8	91.1	91.1
	Rear	96.5	96.5	96.5
	Chamfered	75.3	75.8	75.2
	Rib	77.7	80.4	81.1
	Average	84.2	85.9	86.0
3D		85.4	86.2	86.3

Table 2. ROC-AUC value of machine learning models

Machine learning model	Predict rate [%]	AUC		
		Tension	**Compression**	**Shear**
Decision Tree	85.4	0.95	0.94	0.80
SVM	86.2	0.96	0.94	0.62
k-NN	86.3	0.98	0.97	0.87

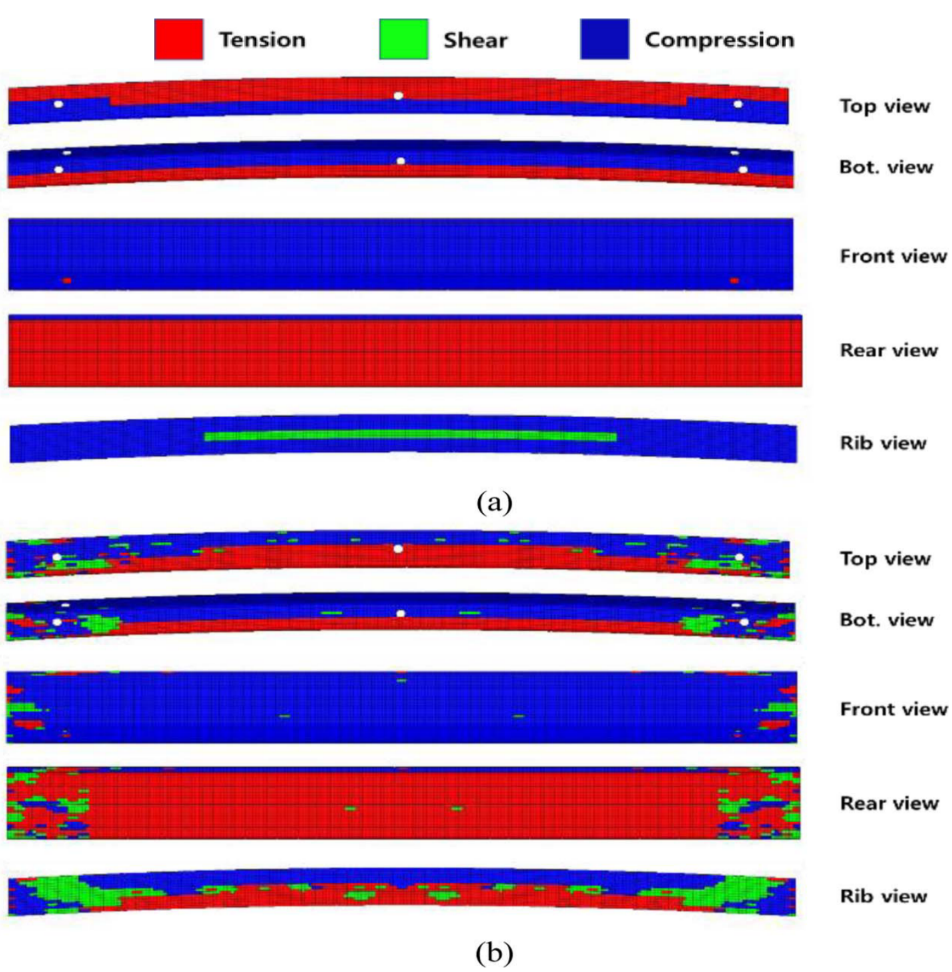

Figure 4. PIC FE model: (a) 2D implementation, (b) 3D implementation

angle sequences known to have high strength for each load type are shown in **Table 3**, and the stacking angle sequences were applied to the elements mapped by load type [17]. The analysis results are shown in **Figure 5** as a force-displacement diagram, the maximum bearing load of the bumper beam designed by the 3D representation method was found to be about 206.2 kN, which is about 12.7% and about 13.1% higher than the bumper beam modeled by the 2D design technique and single stacking order, respectively.

Table 3. Stacking sequence of loading type

Loading type	Stacking sequence
T (tension)	$[90/0/0]_{6s}$
C (compression)	$[\pm5/\pm45/90]_{3S}$
S (shear)	$[0/0/90]_{15}$

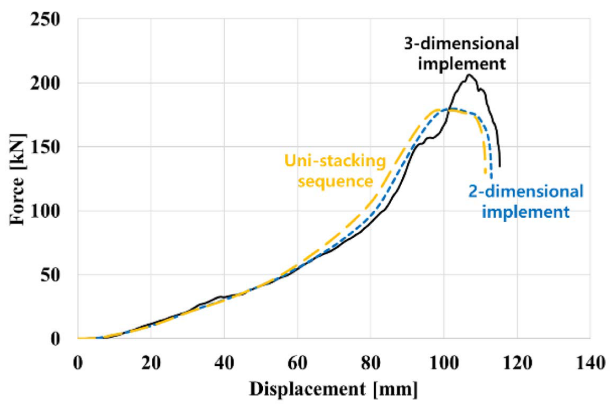

Figure 5. Force-displacement curves

4. Conclusion

In this study, a PIC design method using machine learning techniques was applied to a vehicle front bumper beam with a more complex shape than a simple beam. In order to check the competitiveness of the 2D representation method and the 3D representation method of the training data, the PIC design method using both methods was designed and applied to the bumper beam. The 2D representation method generates training data by dividing the finite element model into each side, and the coordinates of the reference element, which is the input value of the training data, are represented by (x, y). It has the advantage of showing the load type characteristics of each face well. The 3D representation method generates training data for the entire element, and the coordinate value of the reference element is in the form of (x, y, z), which has the advantage of reducing modeling time because it uses one machine learning model. The machine learning models generated by both methods are tuned to the optimal values of hyperparameters by Bayesian algorithm.

The k-NN classification model performed the best in both the 2D and 3D representation methods. To compare the performance of the 2D and 3D representation methods, the average prediction rates of the machine learning model using the 2D representation method and 3D representation method were compared, and the 3D representation method performed better by a small margin.

From the results mapped through the machine learning model, which showed excellent performance, it was predicted that the 3D representation method, unlike the 2D representation method, is affected by the load type of the other side in the part where each side is connected, which is thought to be due to the connection between each side, and the influence of the load type on the other side is considered.

To compare the bumper beam with the 2D representation method and the 3D representation method, the finite element analysis was performed under the same conditions as the previous finite element analysis, and the strength of the bumper beam with the 3D representation method was improved by about 12.7% compared to the bumper beam with the 2D representation method, and it was improved by about 13.1% compared to the bumper beam modeled with a single stacking angle order, which verified the superiority of the 3D representation method.

If the bumper beam designed with the PIC design technique is designed with a similar strength to the bumper beam modeled with a single stacking angle sequence, it is believed that lightweight reduction is also possible. In order to achieve similar strength, it seems that research on how to apply PIC by dividing the thickness of the bumper beam into sections is necessary.

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Disclosure statement

The authors declare no conflict of interest.

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