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A study on the shape shifting composites

Machine-learning assisted design, optimization and prediction

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Abstract

In one part, this paper deals with the simulation of shape shifting composites using finite element methods and checking the direction of fibers in the simulation results. In the other part, the applications of machine learning in predicting the properties and optimizing the design of shape shifting composites that are responsive to temperature and humidity in addition to fiber orientation, are explained.

Article info

Keywords: shape morphing composites, shape shifting materials, machine-learning, finite element analysis

1. Introduction

Dynamic and controllable shape change is one of the newest desirable properties to achieve with engineering materials. Though it is challenging to be achieved, its helpfulness in a vast variety of fields has stirred up interest in mechanics of shape shifting composites among the engineers.

According to the studied articles, a group of researchers, inspired by the perfect shape changes in the wings of the flying birds for aerodynamic efficiency, have been able to develop a group of morphing composites used for various applications such as wind turbine blades, car accessories and aircraft wings and components [1].

In a similar study, development of a morphing wing using macro fiber composites and comparing its performance data with a standard aircraft to determine the better performance was investigated [2].

In another article, the development of hybrid materials by combining living organisms which are embedded inside a polyacrylamide hydrogel was discussed. Controlling the magnitude of the volume change is fulfilled by controlling the cell loading and hydrogel stiffness. An increase in the number of the living organisms inside the composite is also considered a key factor in the further shape change [3].

Bistable composites, which are structures with 2 natural equilibrium states and have the ability to transition between them by a change in shape with minimum energy input, were studied in another article [4]. Main driving methods were considered piezoelectric actuation, thermal actuation, shape memory alloy actuation and magnetic actuation due to their controllability.

In an article related to shape morphing composites [5], bio-based shape morphing polymers were the main focus of the writers. These types of materials are able to recover their original shape with external stimuli such as a change in pH or moisture. Producing this type of material by using 3D printing techniques such as Direct Ink

Writing in order to use the outcome in such products as a programmed stent was also discussed later in this article.

Creating flexible skins is also made possible by using materials with different flexibility in morphing and non-morphing directions. Fishbone active cambers and compliant structures such as the Mission Adaptive compliant wing (MACW) are developed with the intention of controlling aerodynamic pressures which will result in an improved flight performance [1].

Both discrete and continuous shape changes are achievable with varying control and energy requirement. In an unsymmetrical layup with varying coefficient of thermal expansion (CTE) in different plies, the mismatch between the CTEs in longitudinal and transverse fibre directions will result in a generated residual stress when the multidirectional composite is cured at a high temperature [1].

2 layer multidirectional composites with different CTEs in each ply that are exposed to a predetermined temperature are also designed and analyzed with Finite Element Method in the process of this project.

Machine learning is a set of methods and algorithms that allows computers to learn from dataset and apply it to a new data. The last objective of this article is to use machine learning algorithms to predict tensile modulus of flax fiber shape memory epoxy hygromorph composite based on factors such as fiber orientation, temperature and humidity that have non-linear and statistical effects.

Flax fiber shape memory epoxy hygromorph is a bio-composite that includes natural flax as the fiber and epoxy resins as the matrix. The fiber is used due to reinforcement and biodegrability. Epoxy resins are responsive to humidity due to hygromorphic properties and also they have shape memory properties due to the presence of shape memory polymers (SMPs). The mentioned composite is used in self adaptive structures, morphing devices, soft robotics and compliant rigid links (such as exoskeletons), self-healing materials and etc. These materials can change their shape, size or properties in response to external stimuli such as humidity, light, temperature or stress. In this article the effects of 3 parameters on tensile modulus is investigated using 3 different machine learning algorithms. The effective parameters are fiber orientation, temperature and humidity.

Machine learning has many advantages such as high accuracy in predicting the desired characteristics such as tensile modulus, handling large and complex datasets and fewer experimental tests resulting in significant cost and time savings.

2. Finite element analysis

In this part, 4 models of 2 ply composites with different fibre orientations were examined by Abaqus CAE via using finite element method. One of the plies is a unidirectional carbon fibre lamina and the other one is a unidirectional glass fibre lamina.

These 2 laminas were put together with varying fiber angles. The function of the 2 layer laminates were studied under 2 different conditions. Firstly, the change in shape of the composites was analyzed when the composites were exposed to a 60° C temperature. Then the examinations were done when the composites were exposed to a -30° C.

It shall be noted that the coefficient of thermal expansion (CTE) of each layer was considered different in longitudinal fibre direction and transverse to fibre direction. Additionally, as a result of using different fiber materials, the CTEs of each lamina were considered dissimilar.

The mechanical properties of each individual CF and GF laminas are shown in table1 [6]. The figure that the CTE of each lamina was derived from is also presented as Figure1 [6]. It is also important to mention that the initial temperature of the morphing skin was considered 30° C according to the studied article [6].

Table 1. Summary of the physical and mechanical properties of solo GF and CF laminas

	Density ρ [g/cm^3]	Elastic modulus fibre direction E_1 [GPa]	Elastic modulus transverse to fibre direction E_2 [GPa]	Poisson's ratio υ_{12}	Shear modulus G_{12} [GPa]
GF lamina	1.744	34.15	12.33	0.23	3.80
CF lamina	1.541	133.20	7.77	0.3	2.29

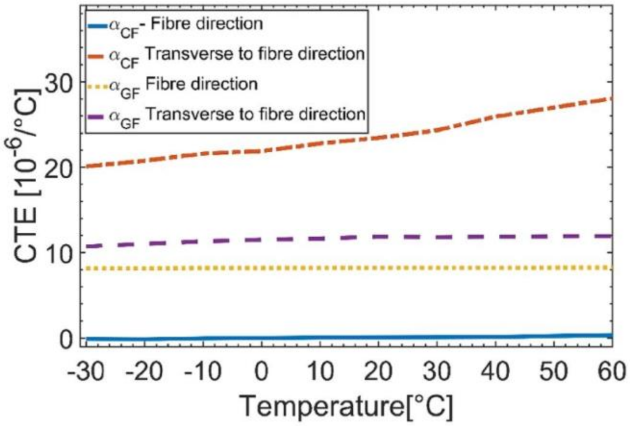

Figure 1. CTE vs temperature curves for CF and GF along and transverse to fibre direction.

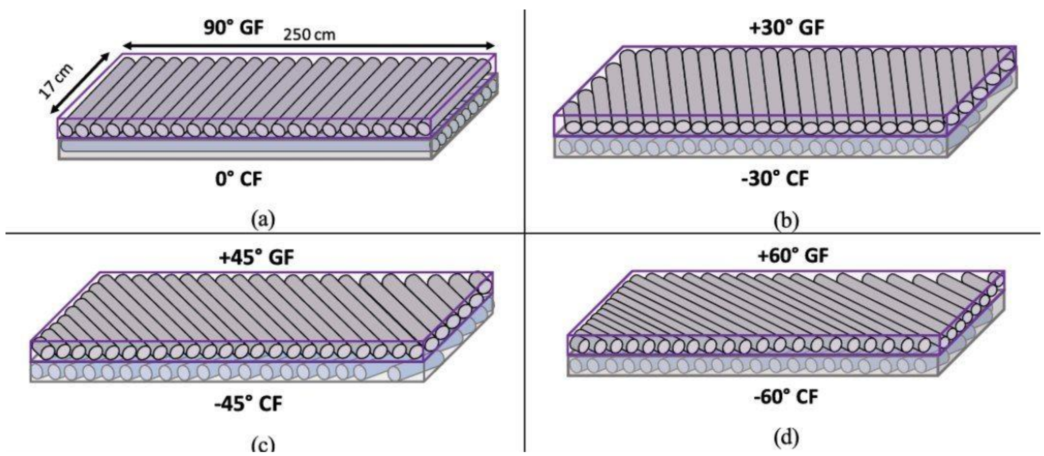

Figure 2. A schematic representation of stacking sequence of CF and GF layers in the laminate.

As it is shown in figure2, the stacking sequences that are examined are as follows:

(a) $[90_G/0_C]$, (b) $[30_G/-30_C]$, (c) $[45_G/-45_C]$ and (d) $[60_G/-60_C]$

The results of the finite element analysis using Abaqus of some of the models are presented in the following page. These figures indicate the resulted shape change and displacement transverse to the modeled laminates. The demonstrated results can be used as optimization tools in the next step in order to attain the superior desirable shape change. Rest of the results will also be presented in addition to this report on the CD.

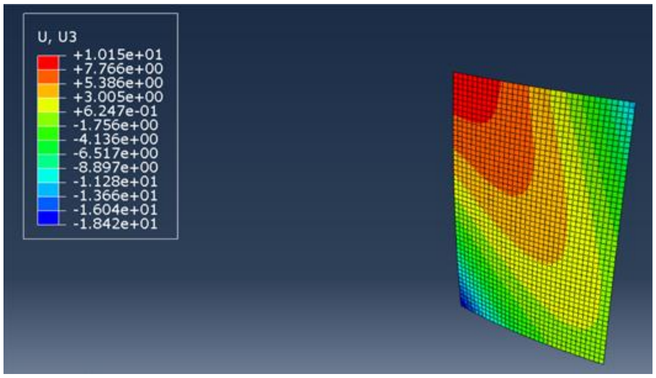

Figure 3. [60_G/-60_C] at -30° C

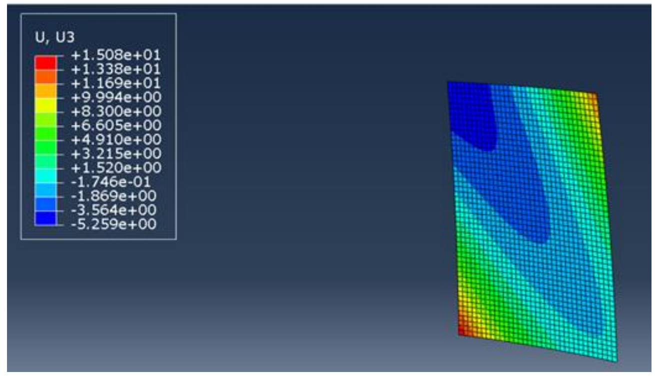

Figure 4. [60_G/-60_C] at 60° C

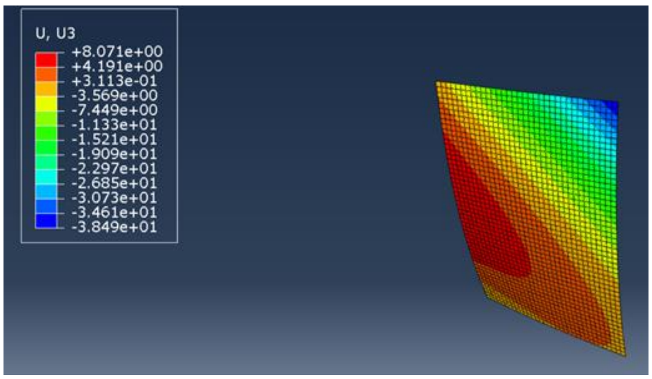

Figure 5. [30_G/-30_C] at -30° C

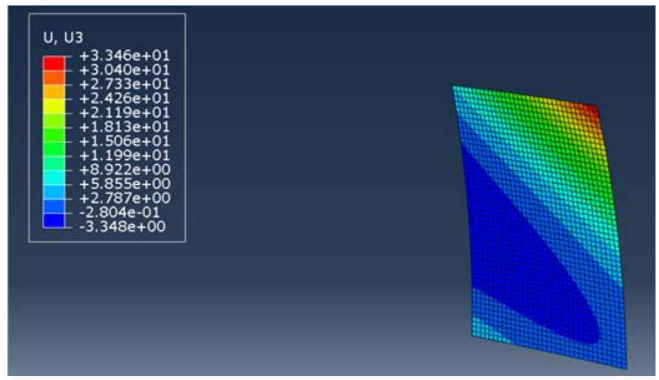

Figure 6. [30_G/-30_C] at 60° C

3. Machine-learning assisted optimization

The first step of machine learning models development is to provide a dataset. The dataset can be extracted from experimental tests or computer simulations mostly in finite element methods. The important factor is the reliability of the dataset that leads to accurate and reliable results.

Experimental data is collected under various conditions by a group of scientists mentioned in one of the referenced papers [7]. Fiber orientation is longitude (0°) or transverse (90°), temperatures are 20, 40, 60, 80 and 100°C and the tested material is 50% humid or fully immersed.

The next step is to train the model using different machine learning algorithms. Machine learning algorithms are mostly considered to be supervised or unsupervised (There is also another field called reinforcement learning that is out of context). Supervised learning is used to train the model based on labeled data and unsupervised learning does the same with unlabeled data. Regression and classification problems are solved using supervised learning methods and unsupervised learning algorithms are useful for clustering problems.

Figure 7. Dataset

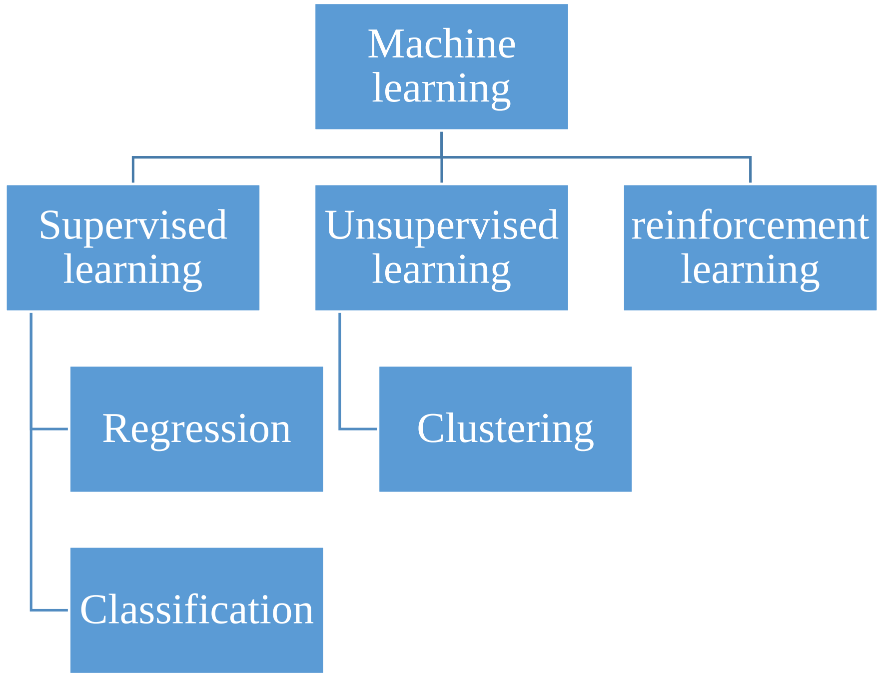

Figure 7. Machine learning problems categorization

Tensile modulus prediction is a regression problem and multiple algorithms can be utilized to satisfy the purpose. In this article 3 famous and powerful supervised algorithms are investigated. These algorithms are Decision Tree, Support Vector Machine (SVM) and Random Forest. Python programming language along with Pandas and Scikit-learn libraries are used to manipulate data and train models based on mentioned algorithms.

The results are based on 2 important concepts in machine learning. One is the coefficient of determination which is called R^2 (R-Squared) and the other is feature importance.

Coefficient of determination specifies how well a statistical or machine learning model fits the data. Its value is between -1 and 1. The closer it is to 1 or -1, the more optimal the algorithm is and if it gets closer to 0, the algorithm becomes more unreliable. Table 2 shows coefficient of determination of each of the 3 ML algorithms used in this article.

Table 2. R-Squared of each algorithm

Algorithm	**Coefficient of determination (R-Squared)**
Decision Tree	0.969057
Support Vector Machine	0.942183

Random Forest	0.968772

Feature importance specifies how important, effective and critical a feature is for predicting the target value. In this case there is a 4 dimensional space with 1 independent variable (tensile modulus) and 3 dependent variables that are 3 features with 3 different feature importance as mentioned before. Table 3 shows every feature importance resulted from each algorithm.

Table 3. Feature importance resulted from each algorithm

Feature importance	Decision Tree	Support Vector Machine	Random Forest
Fiber orientation	0.607056	0.659499	0.598331
Temperature	0.163298	0.151948	0.168610
Humidity	0.229646	0.204031	0.233059

4. Conclusion

For finite element analysis, laminates with 2 CF and GF laminas with thicknesses of 0.27 and 0.2 µm were examined at different temperatures. It was concluded that varying the orientation of the fibers in each ply results in different shape changes and displacement due to different CTEs along the fibers and transverse to the fibers. Then these results were used to fulfill the optimization goals.

The paper also showed that machine learning can be reliable and effective for design of smart composite materials and prediction of their behavior. It was concluded that the coefficient of determination of each algorithm is high and more than 0.9. This means all of the models are well trained and they are reliable. Also the algorithms determined each feature importance and it is obvious that fiber orientation has the most effect on tensile modulus and temperature has the least.

It should be noted that in the future, evolutionary algorithms such as genetic algorithms can be used to optimize the design of shape shifting composites.

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