Method of Predicting the Polymer Composites' Properties Using Neural Network Modeling

D. Vdovin^{1,*}, A. Abramochkin¹, A. Borodulin¹, and V. Nelyub¹

¹Bauman Moscow State Technical University (BMSTU), 105005, Moscow, Russia

Abstract. A neural network modelling technique and its training to diagnose polymer composite materials based on tomography data is introduced. As an object of study, carbon fiber made by vacuum infusion technology using an epoxy binder is considered. X-ray microtomography was used to analyze its structure and the provided images were used as a database for creating a neural network. A neural network modelling technique and its training was developed, including an algorithm for converting tomograph images into data on the structure of the phase composition and the physical and mechanical properties of the object under study.

1 Introduction

Contact molding technologies have been used in composite manufacturing industry for a long time and they are constantly under improvement. Traditionally, they are divided into one-stage, which include, for example, the technology of vacuum infusion and two-stage, where at the first stage – a prepreg is produced, and at the second stage-component is formed from it [1, 2]. A prepreg is a thermosetting molding composition consisting of a binding and reinforcing fibrous material (most often fabric or tape), which requires further curing and is processed into a polymer composite material by various methods [3-5]. The prepreps are widely used in the aviation industry and in the manufacture of rocket and space elements, which is due to the high mechanical properties of the finished products.

However, the prepreg technology has its disadvantages, such as high cost and labor intensity, and therefore prepreps are gradually replaced by the vacuum infusion technology which allows to combine the processes of impregnating the reinforcing material and molding products in a single technological cycle. Initially, only thermosetting materials, most often epoxy, were used as binders in infusion technologies, but in recent years many new types of binders have been developed that are characterized by high mechanical and thermal-physical properties [6-8].

Various methods of non-destructive testing are used to assess the quality of components manufactured by using vacuum infusion technology, including structural analysis methods [8-12]. The detection of internal defects in composite materials by non-destructive methods is an important requirement, both for quality control at the production stage, and for monitoring their durability during operation and maintenance. Non-destructive testing

---

* Corresponding author: vdovin.dims@gmail.com

allows to determine structural defects at a different scale, however, the data obtained in such structural analysis is difficult to interpret due to its discrete nature and often it is only valid for a single area of the material under study.

The purpose of the scientific research is to develop a neural network which will allow predicting the physical and mechanical properties of polymer composite materials with high accuracy.

2 Materials and methods of research

In this study, the SkyScan 1172 X-ray microtomograph was used to analyze the structures of polymer composite materials, which allowed to visualize internal defects and damage that occur during the production or maintenance of products made of polymer composite materials. According to the works [10, 13] it is known that the durability and reliability of parts and products made of polymer composite materials depend on their internal structure and the nature of damage caused by external loads.

As an object of study, one sample of carbon fiber was selected, which was scanned for 5 hours and allowed to obtain 2197 images, which were automatically combined into a 3D image.

Figure 1 shows cross-sections of the 3D image, which do not reflect the true structure of the entire material of study and characterize only one or several of its sections randomly selected. Figure 2 shows examples of 3D images of the same material, which were also randomly selected, since each image is obtained as a result of random reflection in the X, Y and Z axes, their rotation, re-scaling, etc.

Fig. 1. 2D cross-sections of the 3D image

Fig. 2. 3D image

3 Discussion of research results

The neural network allows to replace much of manual labor due to its ability to conduct the analysis of several thousand images, which will eventually lead to automation and faster processing of the results of structural analysis. Furthermore, the use of the neural network in the data processing allows to independently determine typical defects, which will optimize the technological modes of molding specific parts.

Neural networks are used to solve complex image segmentation problems in many areas, such as image visualization in the medical field, face recognition, and autonomous driving [14, 15]. When network models are structured by several consecutive layers of artificial neurons, this method is commonly referred to as deep learning. Convolutional neural networks (CNNs) are a special case of deep learning, where one or more layers of the network perform convolution operations. The deep learning mechanism using the resulting images allows to train specific convolution kernels to extract the corresponding image features that become distinctive features when segmenting characteristics in complex images.

CNNs can be used as image transformation mechanisms that take input data and transform it into segmented images. A CNN architecture can be thought of as a linear weights formula applied to the pixel intensity of an image, often combined across multiple network layers in a non-linear fashion. The coefficients encoded in the neural network itself are extracted from the training dataset, which links the examples of the input images to the examples of the output images. The iterative process of learning weights that can reliably transform input images into output images is called learning, and this is the most computationally complex phase of the deep learning cycle. Segmented training data can be a set of image fragments that have been segmented manually to identify the composition of the material (or label) for each pixel. Subsequently, the trained model can automatically segment the remaining unsegmented image fragments. This process of using the trained model to transform the remaining unvisited image fragments is called inference, and requires less computing power than the training stage.

We also varied the brightness of the image in Fig. 3, which allowed us to visualize internal defects in the form of micropores and microcracks.

Fig. 3. The image with varying brightness

The interface between the polymer matrix and the fiber is a separate, independent phase characterized by its own geometric and elastic properties. It differs from the other phases by its significantly smaller size and more complex structure in the form of a developed topology, the multiphase nature of the polymer matrix and carbon fiber, and many other factors. The structure of the interfacial zone is significantly influenced by technological factors, such as the viscosity and viability of the binder, the permeability coefficient, which in turn depends on the structure of the reinforcing material and the viscosity of the binder, the distance from the supply channels of the binder, the properties of the used auxiliary materials, primarily the conductive mesh.

In the carbon fiber material used as the object of this study, as in all other polymer composite materials made using fibrous fillers, the interfacial zone is the weakest part, due

to the fact that its strength depends on the adhesive bond strength in the polymer matrix-reinforcing material system. Table 1 shows the values of the tensile strength of carbon fiber and the interlayer shear, which exhibits that they differ by several orders of magnitude, thus a simple replacement of the molding technology or the chemical nature of the initial components has no significant effect. As a binder in all carbon fiber plastics (see Table), an epoxy composition based on epoxy resin and an anhydride-type hardener is used.

Table 1. Properties of carbon fiber plastics and their components

Carbon fiber labels	Tensile strength, GPa		Strength of carbon fiber under interlayer shear, MPa
	Carbon Fiber	Carbon plastic	
T700	4500	2050	64
T-300	3500	1400	30
LUP-0,1	2500	1110	56
Elur-0,1P	2400	1020	77

The properties of the strength of carbon fiber plastics under tension and interlayer shear, shown in Table 1, were obtained using the vacuum infusion technology. When it is replaced with prepreg technology and autoclave molding, all the strength properties of carbon fiber plastics increase, to a lesser extent they increase for the tensile strength of carbon fiber (10-25%) and to a greater extent they affect the increase in strength during interlayer shear (it increases by 25-40%). However, regardless of the materials used and the molding technology, the interlayer shear strength values for all carbon fiber plastics are several orders of magnitude lower than corresponding values for the tensile-, compressive-, or bending strength. These data once again proves the great importance of the interfacial layer, since it determines the mechanical properties of the interlayer shift.

The logic of the proposed algorithm is represented by a Figure 4.

Before uploading images to the neural network, they must be pre-processed. Preprocessing is a typical procedure for micro-images, which is mostly aimed at improving the image visualization. Implementation of this stage will ensure high accuracy of the neural network and facilitate further steps, such as segmentation and prediction of material properties.

Pre-processing stage consists of several steps:

- 1) Cropping external areas of the image.
- 2) Automatic contrast enhancement in order to improve the visibility of the phases and reduce the contrast differences between several layers (images) of the test sample that may occur when an image is produced on the tomograph.
- 3) Noise reduction using a non-local mid-and low-pass filter. The boundaries between the phases are much sharper compared to the unfiltered images, which greatly facilitates manual design for training the neural network.
- 4) Comparison of histograms. The contrast of the image may vary due to the different density of the matrices of the two types of materials under study, but this difference in the number and size of voids and fibers does not affect the accuracy of the neural network. However, it was investigated that loading images with different contrast ranges affects the functioning of the neural network. Comparison of histogram can work as the solution to this issue. This method can be used to normalize two images or normalize layers of the same image based on the histogram of the reference input image. In our study, the image used as input to train the network was also used as a reference to normalize the histogram of the images to which the network was applied.

Fig. 4. Algorithm of neural network

The processed images are uploaded to a database, which, in addition to images, stores information about both the composition of the material and the manufacturing technology. All these parameters will be used in the future to determine the physical and mechanical properties of composite materials.

The next stage of the algorithm is to determine the phase composition of the test sample. For this purpose a neural network to identify the pores, filler and binder is to be created. The training database for each current class-pore, filler, and binder-is defined by areas marked up manually from a subset of 2D slices.

The training database was prepared in 10 image slices, as shown in Fig., where the outlined voids, fibers, and matrix are presented in colors, respectively. These marked-up images are then provided as output data for training the network, and the original image is used as input. Semantic image segmentation — marking pixels in an image according to the object they compose — is a deep learning technique that was first applied to scientific visualization with a description of the U-Net architecture. This network model is

constructed as a CNN in which image data is divided into fragments and delivered through a network of neurons located in successive layers. Each neuron in a given layer receives input from the neurons in the previous layer, converts the input signal, and then passes the result to a set of neurons in the next layer. After training, the network can be applied to all slices and/or other images of the same type.

After determining the phase composition of the test sample, you can proceed to the final stage – the determination of the physical and mechanical properties of the Polymer Composite Materials (PCM). By inserting information about the composition, manufacturing technology, and phase composition of the material to the neural network, it is possible to predict the physical and mechanical properties of the PCM with high accuracy using a multiparametric regression model.

4 Conclusions

In this study, a neural network modelling technique and its training based on the results of structural analysis on an X-ray microtomograph as a source database.

As an object of study, carbon fiber made by vacuum infusion technology using an epoxy binder is considered. This technology is inferior in quality to the technology of autoclave molding with the use of prepregs, which is largely due to a presence of a large number of micro - and macro-defects.

To design a neural network, a special technique was developed that includes an algorithm for converting tomograph images into data on the structure of the phase composition and the physical and mechanical properties of the object under study.

The results of this work were obtained within the framework of agreement No. 19/1251/2021 dated 30, 04, 2021 (On the provision of a grant for state support to the centers of the National Technology Initiative on the basis of educational institutions of higher education and scientific organizations).

References

1. Maung P.P., Malysheva G. *Modeling the effect of fabric weaving pattern on the impregnation process in the manufacturing of the fiber reinforced plastic structures*. AIP Conference proceeding. v.2171. (2019).
2. Malysheva G.V., Kirsanova E.A., Mauang P.P., Tumasova M.S. *Rigidity of glass carbon and organic yarns of special-purpose fabrics*. Fibre Chemistry. v.48, № 2. pp. 140-142. (2016).
3. Marycheva A.N., Guzeva T.A., Pe P.M., Tun L.K., Malysheva G.V. *Technologies of production of layered composites*. Russian Metallurgy. № 13. pp.1373-1377. (2019).
4. Borodulin A.S., Marycheva A.N., Malysheva G.V. *Simulation of impregnation kinetics of fabric fillers in the production of fiberglass articles*. Glass Physics and Chemistry, v. 41(6). pp. 660-664. (2015).
5. Chen Ya., Gorodetskii M.A., Nelyub V.A., Malysheva G.V. *Algorithm for the optimization of the technological conditions of forming epoxy-matrix-based composites*. Russian Metallurgy, v. 13. pp. 1369-1372. (2019).
6. Gorodetskii M.A., Nelyub V.A., Malysheva G.V., Shaulov A.Y., Berlin A.A. *Technology of forming and the properties of reinforced composites based on an inorganic binder*. Russian Metallurgy, v. 13. pp.1195-1198. (2018).
7. Malysheva G.V., Shablygin M.V., Guzeva T.A. *Method for assessing aramid fiber microstructure features*. Fibre Chemistry, v. 47 (2). pp. 85-88. (2015).

8. Kobets L.P., Borodulin A.S., Malysheva G.V. *Study of microcapillary impregnation of carbon fibres by epoxy binders*. Fibre Chemistry. 48(4). pp.311-315. (2016).
9. Nelyub V.A., Gorberg B.L., Grishin M.V., Berlin A.A., &Malysheva G.V. *Properties and technology of applying metal coatings to carbon tape*.Fibre Chemistry, v. 50 (6). pp. 524-527. (2019).
10. Baurova N.I., Zorin V.A., Prikhodko V.M. *Influence of structural defects in carbon fibers on their sensor properties evaluated using scanning electron microscopy*. Fibre Chemistry. v.46. №5. pp.283-287. (2015).
11. Baurova N.I., Zorin V.A., Prikhodko V.M. *Determination of the synergetic effect of the damage accumulation process in polymer materials using catastrophe theory*. Theoretical Foundations of Chemical Engineering, v. 50 (1). pp.119-125. (2016).
12. Baurova N.I., Zorin V.A., Prikhodko V.M. *Accuracy of diagnosis of metal structures using carbon fibers*. Fibre Chemistry. v.48. №6. pp.504-506. (2017).
13. Baurova N., Anoprienko A., Romanova Y. *Providing dismountable rivet bonded joints through the use of hot-melt adhesive*. ICMTMTE. v. 129. (2017).
14. Baurova N.I., Makarov K.A.*Machining of machine elements made of polymer composite materials*. Rission Metallurgy. №13. pp..1141-1144. (2017).
15. Yuanyuan Wang Shuhong Chai, Hung Duc Nguyen *Experimental and numerical study of autopilot using Extended Kalman Filter trained neural networks for surface vessels*. International Journal of Naval Architecture and Ocean Engineering. v.12. pp. 314-324. (2020).