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APPLICATION OF NEURAL SIMULATION METHODS FOR TECHNOLOGICAL PARAMETERS IDENTIFICATION OF COMPOSITE PRODUCTS INJECTION MOLDING PROCESS

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The article presents the research results of technological parameters of composite material products manufacturing by the injection transfer molding method using automated tools of preproduction engineering. For the verification of computer simulation results, experimental studies have been carried out on the injection-molding machine for products from fibrous polymer composite materials. The conducted comparative analysis of calculated and actual values of impregnation technological parameters has led us to the conclusion that for the effective application of the modern software for preproduction engineering of composite products it may be necessary to make a joint correction of the input data used for the calculation obtained from the preliminary independent experimental research of the complex of properties for each used component of the composite material. For the joint correction of the input data used for the calculation and improvement of the efficiency of automation systems for preproduction engineering of composite products, the concept of the neural simulation tools application for the technological process of composite products manufacturing by injection molding methods has been proposed. For training and testing of the neural model, experimental studies of the impregnation of the products with the surface curvature of the second order have been conducted. The optimization problem was solved by forecasting the front movement of the technical fluid in the volume of preforms during transfer molding.

Key words: automation of technological processes, tools of preproduction engineering, polymer composite materials, injection-transfer molding, finite element analysis, neural simulation, optimization

INTRODUCTION

In many sectors of modern industry, especially in aviation, automobile and space industries, in shipbuilding and construction, the need for critical products has been increasing, as noted in works [1, 2]. Such products are subject to strict requirements in terms of mass-dimensional performance and reliability. Often polymer composite materials (PCM) are used to reduce weight characteristics of products [22, 23]. However, the ever-increasing manufactured products range and increasing scope of products from PCM leads to changes and complication of their manufacturing technologies resulting in an increased risk of production defects such as non-impregnated zones, pore and crack formation, layer separation and warping of the manufactured product, as shown in works [3, 4]. The formation of any of these defects can lead to a reduction in reliability, service life decrease and subsequent destruction of the operated product. One of the main reasons of defect formation in PCM is inefficient process conditions of their manufacturing, as demonstrated in paper [5], i.e. preliminary preproduction engineering is required, as is proven in paper [6].

For today at many enterprises, which are engaged in manufacturing of composite materials, methods of preproduction engineering are applied which are based on the experimental selection of process conditions according to works [5, 6]. However, this process is expensive, long, and above all not universal because the selection of conditions is carried out each time only for one product, one manufacturing technology and one set of PCM components. Modern automation systems of manufacturing activity represent software packages, allowing carrying out an estimation of the full life cycle of a product from designing to manufacturing, operation and recycling. Such software packages include computer-aided design systems (CAD-systems), computer-aided engineering systems (CAE-systems), solution systems for centralized engineering product data management (PDM-systems) and computer-aided preproduction and manufacturing systems (CAM-systems), as shown in paper [7]. The main purpose of the present research was the estimation of the efficiency of commercially available decisions for the computer-aided preproduction engineering systems of products from composite materials by the injection transfer molding method.

LITERATURE REVIEW

For technological preproduction, CAE-systems are applied, and one of the most top-requested for the simulation of technological processes of composite structures manufacturing by liquid molding methods is PAM-RTM software of ESI GROUP French company, as noted in the market report [7]. This program is designed to solve

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a wide range of tasks related to the simulation of production processes of liquid composite molding. During the calculation, the user generates the optimal product molding design, varying, if necessary, the binder feed or discharge circuit, the location of vacuum ports, composite lay-up, materials, binder, temperature conditions, etc. Simulation results include the forecasted front of the binder distribution, dry zones, product porosity, and pressure field, degree of polymerization, time and velocity of the product impregnation.

This software product uses the finite element method (FEM) as a solver, as demonstrated in paper [8]. To determine the technological parameters of the capillary-porous materials impregnation, the mathematical model of mass transfer is used, which in general case according to papers [8-10] represents the following system of differential equations (1):

$$\begin{cases} \dfrac{du}{d\tau} = D\cdot\delta\cdot\nabla^2 T + D\cdot u\cdot\nabla^2 + D\cdot\delta_P\cdot\nabla^2 P; \\ \dfrac{dT}{d\tau} = \left(a + \dfrac{D\cdot\delta\cdot r\cdot E}{c}\right)\nabla^2 T + \dfrac{r\cdot E}{c} D\cdot\nabla^2 u + \dfrac{r\cdot E}{c} D\cdot\delta_P\cdot\nabla^2 P; \\ \dfrac{dP}{d\tau} = -\dfrac{E}{c_B} D\cdot\delta\cdot\nabla^2 T - \dfrac{E}{c_B} D\cdot\nabla^2 u + \left(a + \dfrac{E}{c_B} D\cdot\delta_P\right)\nabla^2 P; \end{cases} \quad (1)$$

where u, T and P are gradients of relative concentration, temperature and pressure; τ is time; D is the effective diffusion coefficient; δ is the thermal-gradient transport coefficient of impregnating composition; δ_P is the relative coefficient of the filtration flow; c_B is the air specific heat in the capillary-porous medium (fiber preform); a_P is the convective diffusion coefficient; E is the phase transition criterion.

METHODOLOGY

For the study of technological process parameters of PCM products manufacturing, the model of the double-diameter cylinder has been made. Its height is equal to 100 mm, and its cross-sections have different diameters of 40 mm and 20 mm. The wall thickness of the model was taken to be equal to 1.5 mm, which corresponded to a package consisting of four layers of the material. In PAM-RTM software, seven different laminated packages (preforms) were simulated in the model volume, with the following lay-up angles: : $(0°/\pm15°)_4$; $(0°/\pm25°)_4$; $(0°/\pm35°)_4$; $(0°/\pm45°)_4$; $(0°/\pm55°)_4$; $(0°/\pm65°)_4$; $(0°/\pm75°)_4$.

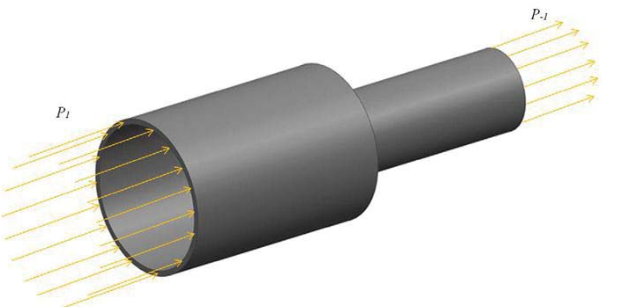


Figure 1: The computational pattern of the sample impregnation process simulation

When modeling the impregnation processes, the matrix material was fed uniformly across the model entire end surface of the larger cylinder base, and air and the excess binder was pumped out from the opposite (symmetrical) side of the model (Fig. 1). Matrix material was pumped under pressure of P_1 = 100 kPa at a temperature of T = 55ºC. Air and the excess matrix material was pumped out under pressure of P_{-1} = 10 Pa.

For parameter calculations of the test model injection molding technological process of the double-diameter cylinder, we assigned the characteristic values of the composite material components presented in Table 1, typical for polymer binder and carbon reinforcing agent, respectively.

Table 1: Properties of the materials used

Material	Density, kg/m³	Dynamic viscosity, Pa·s	Permeability in the directions of the Cartesian coordinate system, m²		
			x	y	z
Polymer binder	1200.0	0.004	–	–	–
Carbon reinforcing material	1800.0	–	$1.0\cdot10^{-10}$	$5.0\cdot10^{-11}$	$5.0\cdot10^{-9}$

In order to increase the accuracy of the impregnation process simulation, the optimization of the finite element division of the double-diameter cylinder three-dimensional model was carried out. The size of the element after the optimization was 2.0 mm, and the total number of elements was 13922. Because of the finite-element simulation of injection molding in PAM-RTM software product, values of maximum and minimum impregnation rates of the double-diameter cylinder models and the total impregnation time of each model were obtained. The maximum and minimum impregnation rates of different types of preform lay-up in the double-diameter cylinder model are presented below (Table 2).

Table 2: Comparison table of impregnation calculation results of the double-diameter composite preform model with different lay-up structures

Reinforcing material lay-up options	Front movement velocity of the polymer binder, m/s		Total preform impregnation time, s
	max	min	
$(0°/\pm15°)_4$	$1.49\cdot10^{-3}$	$4.84\cdot10^{-6}$	108.45
$(0°/\pm25°)_4$	$1.34\cdot10^{-3}$	$4.62\cdot10^{-6}$	115.19
$(0°/\pm35°)_4$	$1.22\cdot10^{-3}$	$4.50\cdot10^{-6}$	120.02
$(0°/\pm45°)_4$	$1.18\cdot10^{-3}$	$4.45\cdot10^{-6}$	121.94
$(0°/\pm55°)_4$	$1.12\cdot10^{-3}$	$4.38\cdot10^{-6}$	124.82
$(0°/\pm65°)_4$	$1.06\cdot10^{-3}$	$4.12\cdot10^{-6}$	132.53
$(0°/\pm75°)_4$	$1.01\cdot10^{-3}$	$3.95\cdot10^{-6}$	156.71

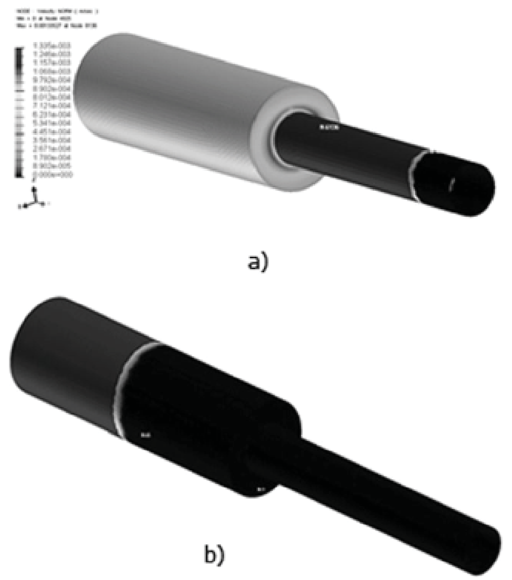


Figure 2: Distribution of binder movement velocities by volume of the preform model:
a) at the time t = 96 s; b) at the time t = 20 s

A typical view of the results of the injection moulding simulation is further presented graphically in Fig. 2a and Fig. 2b by the example of the double-diameter cylinder model – composite preform with $(0^o/\pm35^o)_4$ lay-up.

To verify the results of the computer simulation of injection molding, experimental models of various preforms of double-diameter cylindrical shells consisting of four layers of the fibrous reinforcing material were impregnated. These work-pieces have been produced by triaxial radial winding on a metal double-diameter mandrel of the carbon tape (Table 1) at the different reinforcing angles, which correspond to the following lay-up options: $(0^o/\pm15^o)_4$; $(0^o/\pm25^o)_4$; $(0^o/\pm35^o)_4$; $(0^o/\pm45^o)_4$; $(0^o/\pm55^o)_4$; $(0^o/\pm65^o)_4$; $(0^o/\pm75^o)_4$ described earlier (Table 2).

The experimental models were impregnated on a transfer-molding machine for products from fibrous polymer composite materials described in paper [11]. The polymer binder with properties specified in Table 1 was used as a matrix material. The use of the transfer molding machine for products from fibrous polymer composite

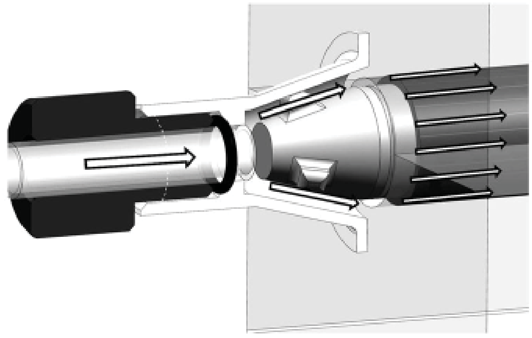


Figure 3: Scheme of the binder distribution during the preform impregnation using experimental tooling

materials has resulted in the technological conditions of the injection impregnation (Fig. 3), corresponding to the initial conditions set in PAM-RTM software product. In turn, it makes it possible to compare the calculated and experimental results of the study of impregnation technological parameters.

In the result of experimental studies, the total time of the complete impregnation of preforms with the matrix material was determined (Table 3). From the comparison table of the results obtained in the experimental studies and computer simulation of the impregnation process, it can be seen that the actual value of the total impregnation time of the double-diameter workpiece during full-scale testing significantly differs from the same values obtained in the result of the computer simulation.

To estimate the accuracy of the injection moulding simulation results of the double-diameter cylindrical model, the error of technological parameters in relation to the actual values obtained in the result of the experiment was calculated. The error was calculated according to the formula (2):

$$p_i = \frac{f_i - f_i'}{f_i} \cdot 100\,\% \qquad (2)$$

where p_i is the error of the i-th technological parameter; f_i is the experimental value of the technological parameter; f_i' is the calculated value of the technological parameter, obtained as a result of the simulation in PAM-RTM software product.

Table 3: Comparison table of results obtained in experimental studies of injection moulding technological characteristics of double-diameter cylindrical models from PCM

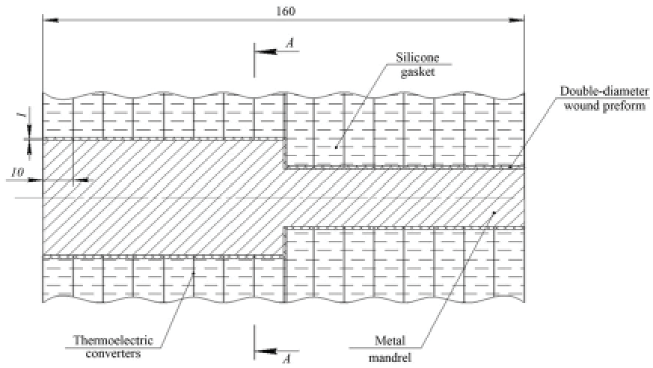
No.	Reinforcing material lay-up options		Total time of preform complete impregnation, s	No.	Reinforcing material lay-up options		Total time of preform complete impregnation, s
1	Simulation	$(0^o/\pm15^o)_4$	108.45	4	Experiment	$(0^o/\pm45^o)_4$	315.18
	Experiment		289.64	5	Simulation	$(0^o/\pm55^o)_4$	124.82
2	Simulation	$(0^o/\pm25^o)_4$	115.19		Experiment		329.25
	Experiment		298.72	6	Simulation	$(0^o/\pm65^o)_4$	132.53
3	Simulation	$(0^o/\pm35^o)_4$	120.02		Experiment		334.24
	Experiment		305.90	7	Simulation	$(0^o/\pm75^o)_4$	156.71
4	Simulation	$(0^o/\pm45^o)_4$	121.94		Experiment		339.41

The main parameters of the injection molding process of the double-diameter cylinder have been determined by the computer simulation method in PAM-RTM software product. To estimate the accuracy of the calculated data, experimental studies have been carried out, which resulted in determining the average error of injection molding parameters. The error values are in the range from 53.82% to 62.55% for the total preform impregnation time.

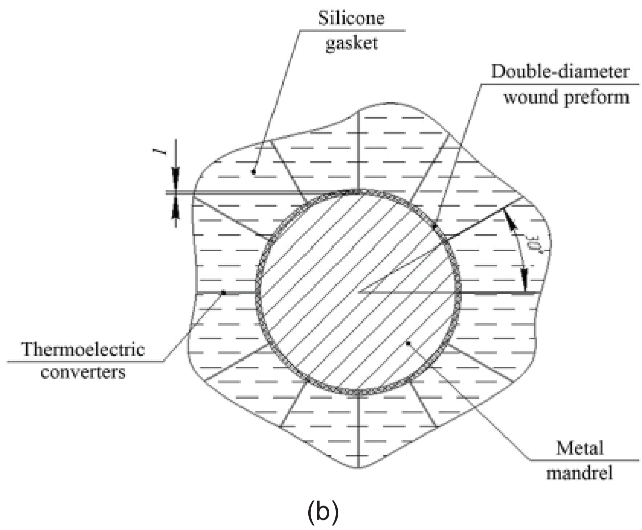
Based on the results obtained, it can be concluded that the errors of the target parameters arise from the simulation complexity of the manufacture of products from composite materials by injection molding methods, requiring the consideration of many factors. The most significant ones are bulk polymerization of the binder and change of its viscosity in the process of compounding and impregnation, the fabric pliability and permeability of the fibrous preform, as demonstrated in papers [12-14]. Each of these factors has a direct impact on the technological parameters of the impregnation process, and lack of their consideration in the simulation leads to a wide disagreement between the results of the simulation and actual values, as shown in works [8, 15]. As can be seen from the above, the application of existing software solutions to automate the preproduction engineering of products from composite materials can be ineffective without conducting preliminary experimental studies to determine the full range of characteristics of the moldable materials, as is proven in paper [16]. However, due to rapidly developing information technologies, it becomes possible to predict the evolution of the matrix material front by using artificial neural networks (ANNs), which can simulate complex or implicit dependencies according to papers [17-19]. For minimization of the simulation error of transfer molding processes using automated tools of preproduction engineering of PCM products in the absence of a priori accurate data for the simulation, the ANN is proposed and tested in this paper.

The configuration of the ANN takes place through training, during which the synaptic scales and neural network topology are adapted so that the output signals meet some predefined quality criterion, as shown in paper [19]. The artificial neural network has the adaptive feature, due to which the synaptic scales are adapted to changes in the "environment" during the training process. In order to utilize fully the advantages of adaptability, it is necessary to form a database consisting of a set of input and output signals. The forecasting of the impregnation process of fibrous products by injection molding methods can be made by the area of the matrix material propagation in the work-piece volume. In this case, the input signals for the neural network are the impregnation time and viscosity of the binder, and the output signals are the area of the binder impregnation in the preform volume. To form a database with the parameters of the impregnation process, a series of experiments have been carried out to determine the boundaries of liquid distribution in the volume of the reinforcing material. As work-pieces for the study of technological parameters were used preforms wound by triaxial radial winding method on the metal double-diameter mandrel at different reinforcement angles with different material lay-up of $(0°/\pm15°)_4$; $(0°/\pm25°)_4$; $(0°/\pm35°)_4$; $(0°/\pm45°)_4$; $(0°/\pm55°)_4$; $(0°/\pm65°)_4$; $(0°/\pm75°)_4$. Technical fluids of various viscosities from 44 mPa·s to 215 mPa·s were used for the impregnation of the work-pieces. The study of the impregnation process parameters of double-curved surfaces was carried out on the transfer-molding machine equipped with a special registration system described in works [11, 16].

The determination of distribution boundaries of technical fluids in the volume of wound preforms was carried out using a system consisting of sensors and a recording device. TP-0198 thermocouples installed in various control points over the whole area of the preform surface were used as temperature sensors (Figures 4, 5). The thermocouples were installed perpendicularly to the cylindrical surface of the metal mandrel in the radial direction at a pitch of 30 degrees and along the axis of the preform at a pitch of 10 mm. In total, 192 temperature sensors were installed (Figures 4, 5). The thermocouples were pressed into a silicone seal to fix the sensors and to ensure a tight installation. The working height of the contact pair of each sensor was 1±0.5 mm (Figures 4, 5).

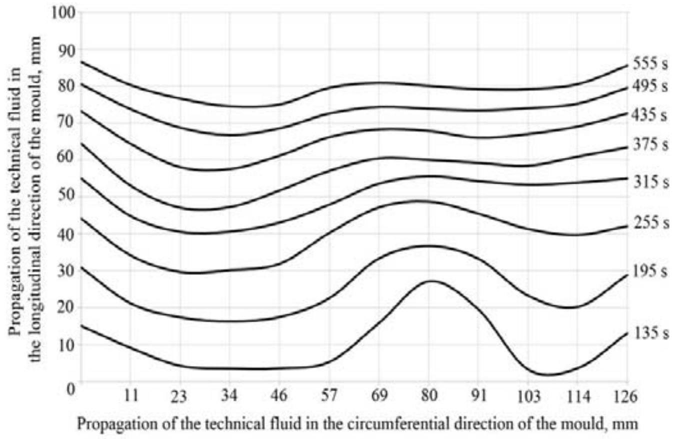


(a)



(b)

Figure 4: Schematic representation of the temperature sensors location: a) in the longitudinal direction; b) in the transverse direction



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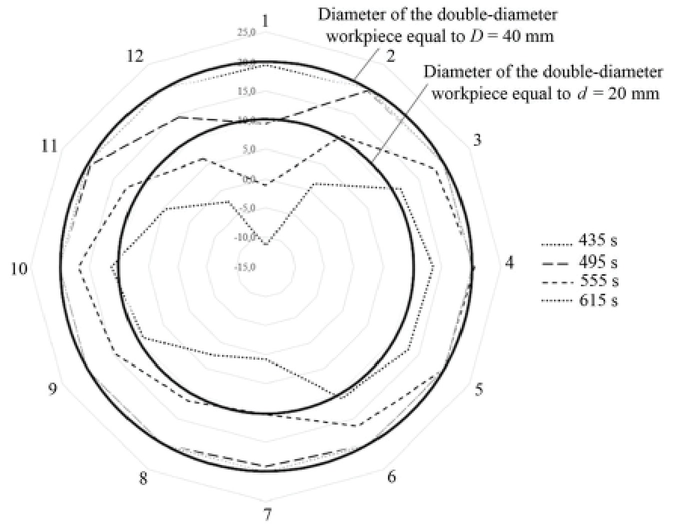
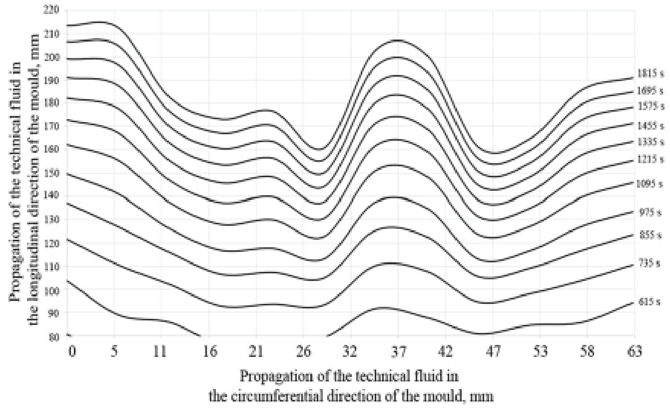
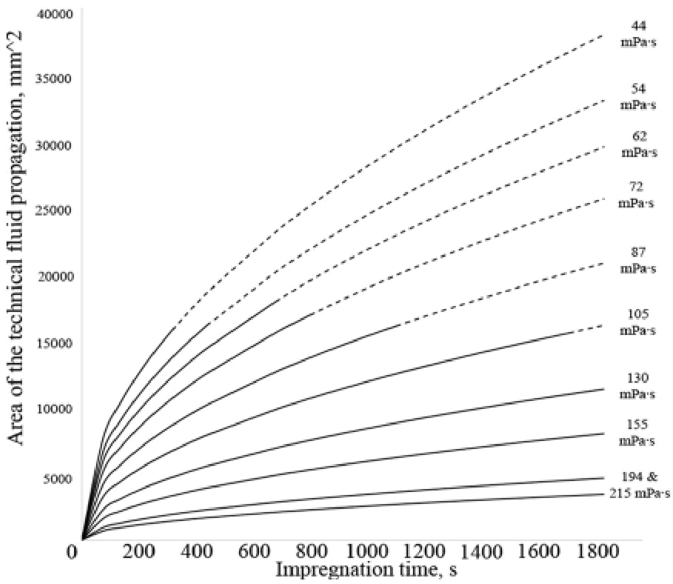


(b)

Figure 5: Interpretation of the technical liquid distribution in the volume of the double-diameter cylindrical preform: a) the net of a cylinder with D = 40 mm; b) the end surface of the double-diameter cylindrical preform



(a)



(b)

Figure 6: a) interpretation of the technical liquid distribution in the volume of the double-diameter cylindrical preform (the net of a cylinder with the diameter d = 20 mm); b) integral interpretation of the process of the technical liquids front line evolution of different viscosity in the volume of the preform with lay-up of $(0^o/\pm45^o)_4$

During the impregnation of the tubular work-pieces, the technical fluids were in contact with the working surfaces of the thermocouples, which in turn recorded the temperature change. The software recorded the time at which this change took place. Time intervals corresponding to the temperature change indications of each thermocouple characterize the process of the technical fluid front movement in the preform volume (Figures 5, 6).

Summing up what has been said, because of a number of experiments, time sampling of the impregnation process of wound work-pieces with technical fluids of different viscosity values was obtained. The obtained sensor response time values were interpreted into diagrams of the technical fluid front movement in the preform volume. The diagrams of the technical fluid front propagation with viscosity 155 mPa·s in the sample volume with lay-up of $(0^o/\pm45^o)_4$ are presented below as an example.

To create an artificial neural network it was necessary to determine the number of layers and the number of neurons in each of these layers, as it was shown in papers [17-19]. The chosen architecture of the applied ANN is a two-layer network with a direct connection consisting of linear output neurons and a hidden layer of neurons with a sigmoid logistic activation function. This ANN is suitable for multi-dimensional mapping tasks when setting the agreed data and having a sufficient number of neurons in the hidden layer. The input layer does not perform any functional calculations being the separation layer of the input signal components. The dimension of the neural network input layer is determined by the dimension of the input signal (the number of parameters supplied to the neural network input). In the task under consideration, the values of the viscosity of the technical fluid used and the impregnation time of the double-diameter preform were selected as neurons of the input layer. The selection of the number of neurons for the output layer is similar to the approach for the input layer: the number of neurons is fully determined by the dimensional value of the output signal. The output layer of the ANN used will contain one neuron, the value of which will determine the area of propagation of the matrix material in the volume of the double-diameter laminated preform. Designing and working with the ANN was carried out using the Deep Learning Toolbox module in the Matlab software environment described in [20]. The architecture of the ANN used is presented in the diagram of Fig. 7. Training of the ANN was carried out according to the Levenberg-Marquardt conjugate gradient algorithm analyzed in paper [21]. The algorithm stopped its work when at the next step of iteration the increment became less, than the specified one. The selected values of weights are sought-for. The applied method has a high sensitivity to initial weights but provides the best quality of training among other analogues.

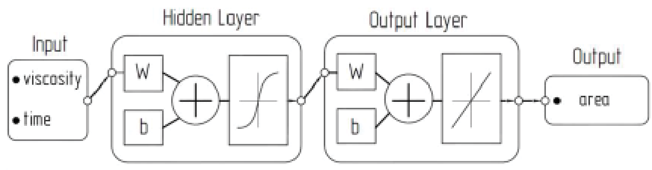


Figure 7: The ANN Architecture in the Deep Learning Toolbox: w – the synapse weight, b – the offset

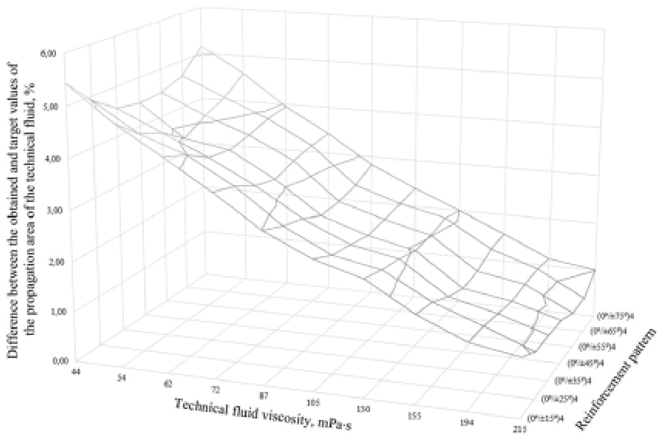


Figure 8: The difference between the values obtained by the neural simulation and actual (experimental) values of the propagation area of the technical fluid in the preform

RESULTS AND DISCUSSION

The values of the technological parameters presented in Fig. 5, 6 were used as input parameters for the neural network, and the obtained results of the trained ANN operation have been compared with the corresponding values of the process fluid viscosity. In addition, the regression of the neural network output data relative to the initial values has been determined. The total convergence of the obtained values in the samples was 98.15%. To check the neural simulation results, a test sample with pairs of initial values and obtained values of the technical fluid propagation area in the volume of the double-diameter cylindrical preform has been prepared. As can be seen from Fig. 8, the difference between the obtained values in the neural simulation, and actual (experimental) values of the technical fluid propagation area in the preform volume is varying from 0.87 % to 5.44 %. From the diagram presented in Fig. 8, we can also see that all material layups are characterized by a decrease in the difference between the obtained values during the simulation and the actual values of the experimental studies. The implication is that with the increasing impregnation rate (decreasing viscosity) the error of neural simulation results and actual technological parameters of the impregnation increases.

CONCLUSIONS

In the result of the research of impregnation processes of double-diameter fibrous products with a surface of the second order it has been found that because of a considerable error of results of the simulation, the application of existing software automation tools of preproduction engineering of products from composite materials are ineffective in the absence of verified input data for the simulation. Thanks to the application of the neural network forecasting model of the impregnation process of the tubular double-diameter product by a transfer molding method developed during the research, the total convergence of the obtained values has reached 98.15%, and the difference between the calculated and experimental values of the impregnation area of the matrix material propagation varied from 0.83% to 5.44%. Thus, by the example of the multilayer double-diameter cylindrical preform, it has been shown that the use of the neural simulation can significantly reduce the forecasting error of the technological characteristics of the impregnation and can be used for the simulation of the manufacturing process of fiber composite materials by injection molding methods.

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