Evaluation of the vacuum infusion process objectives at the early stages of computer simulation

J-P Huang1, I Zhilyaev2, N Snezhina3 and S Shevtsov4

1Dept. of Mathematical Modeling, Southern Federal University, Rostov on Don, Russia
2Institute of Polymer Engineering, The University of Applied Sciences Northwestern Switzerland FHNW, Windisch, Switzerland
3Dept. of Aircraft Engineering, Don State Technical University, Rostov on Don, Russia
4Dept. of transport, composite materials and structures, Southern Center of Russian Academy of Science, Rostov on Don, Russia.

E-mail: sergnshevtsov@gmail.com

Abstract. Increasing the quality and reliable reproducibility of large-size composite structures molding using the vacuum infusion method, which is gaining popularity in various industries, is achieved in practice through numerous tests by try and errors that require significant costs and time. The purpose of these tests is to determine the layout of the ports for the resin injection and vacuum supply, as well as the temperature regime that ensures the absence of isolated non-impregnated zones, the minimum porosity and the required reinforcement volume fraction in the composite. The proposed approach removes the simplifying assumptions used in commercial software for modeling the process, which reduce the accuracy of reconstruction of its dynamics and the sensitivity to the formation of unrepairable defects such as dry spots. It involves multiphysics modeling of resin filling in a porous preform by describing the resin front dynamics by the phase field equation, pressure distribution in an unsaturated porous medium by the Richards equation, the evolution of the degree of cure by the convection / diffusion / thermokinetics equation, and thermal processes by the heat transfer equation using modified models of viscosity, the diffusion coefficient of the degree of cure, the boundary condition for the vacuum port. To reduce the finite element computation time of the investigated variants of the process, which is necessary for its computer optimization, the predictive partial sub-criteria were used, which give a reliable prediction before the beginning of the resin gel and solidification. Due to this, a gain in computation time is 30-50% with a significant prediction accuracy of quality objectives and the presence of possible defects.

1. Introduction

The simplicity and low cost of industrial implementation of methods for molding composite structures based on vacuum infusion technologies has aroused increased interest in them in various industries [1-3]. However, the strong susceptibility of the resulting quality indicators of the process to a change in its scheme (the location of the liquid resin gates and vacuum vents), the temperature regime deteriorates the stability, which prevents its expanded use in practice. Most often, such irreparable defects appear in the form of insufficiently resin-impregnated zones of the preform or the so-called
inner and outer dry spots [4-8]. Replacement of the materials consuming and labor-intensive method of trial and error in choosing a rational scheme and technological modes became possible after the appearance of computer modeling systems for infusion processes, which are a complex of such coupled phenomena as mixing of moving fluid streams of variable viscosity in a porous medium with varying permeability during the process, thermokinetic and rheological transformations of liquid (usually thermosetting) resin under the influence of temperature over time, convective and diffusion processes in continuously polymerized resin [9-11]. All the systems of computer modeling of infusion technologies developed to date and used in practice are based on the so-called Finite Element /Control Volume (FE / CV) method, which makes it possible to overcome the difficulties of modeling a process with a moving interface between two media - liquid and air, and the Darcy’s equation describing the fluid flow rate in completely saturated porous medium. However, the first component significantly degrades the geometry of the spreading resin front, requiring very fine mesh partition, while the second component does not take into account incomplete saturation, especially at the interface. These factors significantly degrade the accuracy and sensitivity of this process modeling method, which, moreover, has great computational complexity. Nevertheless, until now, on its basis, systems are being developed designed to optimize the quality of the infusion process and increase its productivity, i.e. reducing the time of filling the preform with resin [12-17]. To improve the accuracy of reconstruction of the spreading resin front and to improve the sensitivity of the modeling algorithm to the formation of defective non-impregnated zones of the preform when optimizing the infusion process, the authors of this article proposed and implemented a different approach in the environment of a finite element package [18, 19]. This approach is based on the description of the coupled problem by the phase field equation when determining the distribution pressures in the preform, taking into account its incomplete impregnation, the evolution of the thermokinetic and rheological state of the moving resin, which releases exothermal heat.

The noted multiphysics nature of the forward problem of modeling vacuum infusion, as well as its multiscale nature, that is, an extremely large number of degrees of freedom, due to the complex geometry of real composite structures and a large number of interacting phenomena occurring in the process, make it relevant to develop tools that minimize the computation time of process modeling to its completion.

The urgency of this problem has increased significantly in recent years due to the study of such very complex processes in business, biology, social systems, when it is necessary to process large amounts of data and quickly make decisions based on the results of such processing. Technological advances in computer hardware (faster processors, more memory and advanced architecture), as well as new technologies for processing structured data, have made some progress in solving this problem. Along with this, the field of informatics, working with large amounts of data and time series, has received significant development. It uses so-called predictive models that describe the relationship between known input data and a solution in order to predict the final objectives. These models are used to optimize the final results.

Explanatory modeling assumes that a set of factors, as measured by the X variables, produce the main effect as measured by the Y variable. Such an explanation is a causal explanation, and explanatory modeling is the use of models to identify and / or test causal relationships. The theory of such models itself provides causation.

Predictive modeling is defined as the process of applying a model or mining algorithm to data in order to predict new or future observations. This definition also includes temporal prediction, in which observations up to time t (input) are used to predict future values at time t + t1, t1> 0 (output). A predictive model can use any method that makes predictions, regardless of the underlying approach: analytical, numerical, Bayesian or frequency-based, parametric or non-parametric, data mining algorithm, or statistical model. However, predictive modeling in fields of science, the theory of which is rather poorly developed, uses a simple statistical analysis of the results of numerous observations [21-24]. Wherein, the choice of the algorithm was carried out in each work experimentally.
The system considered in this work is a very important example that allows the application of explanatory modeling using an adequate and numerically stable solution at the first stages of the process (preform filling), when the simulation process is carried out fairly quickly. At the final stage of the process, when the viscosity of the resin increases significantly, and the speed of its movement and the speed of simulation of the process slow down, it is the predictive model that is used, which, without giving the obligatory physically accurate description of the ongoing processes, gives a reasonable forecast of the quality indicators of the process in minimal computation time. This approach is implemented using finite element modeling of a non-stationary vacuum infusion problem at the first stage of the process and regression analysis to predict its objectives at its final stage. Such modeling method has substantial advantages when using a software product based on it in optimization tools, but its implementation requires a significant number of preliminary computational experiments.

Below are the main stages of the implementation of the predictive approach used for the early assessment of the target criteria of the infusion process. They include a brief description of the forward modeling problem statement, with an emphasis on its differences from the traditionally used model descriptions. Based on the analysis of the simulation results, performed with variations in the parameters of the process layout and the mode, the possibility of optimizing its quality and performance is estimated. Then, the selection of representative partial criteria is performed, which correlate with the final criterion, and the points in time are selected when the final and partial prediction criteria can be evaluated. Based on the analysis of cross-correlation of a group of partial criteria, those of them are selected that directly characterize the final quality objective and the reliability of its achievement. These partial predictive criteria are combined to form a generalized quality criterion, the use of which is most convenient when solving the inverse problem of process optimization. Finally, an estimate is made of the reduction in computation time due to the use of a predictive approach by comparing the results of a group of simulations.

2. Statement of the modeling forward problem: The governing equations and system properties

The formulation of the modeling problem, briefly outlined below, corresponds to the most common process scheme, in which several layers of glass or carbon fabric are laid on an open mould with geometry of arbitrary complexity. The preform, possibly of varying thickness, is covered with a flexible vacuum bag and sealed around the perimeter to prevent outside air from entering the preform. One or more injection ports of the liquid resin at atmospheric pressure, or runners, as well as vacuum ports are introduced into specific locations of the preform, then the vacuum pump is turned on. The resulting pressure difference across the preform forces the resin to move towards the vacuum port. The spread of liquid resin occurs during its continuous curing and changes in viscosity, changing pressure in the preform, depending on its local filling with resin. The compressibility of a preform can depend on its state (dry or wet), internal pressure in it, and the anisotropy of its permeability depends on the stacking sequence and the anisotropy of the layers. However, in our model of the process, the layered structure of the preform is not taken into account - it is considered as a homogeneous porous material. The evolution of the moving resin is described by the phenomena of convection, thermal kinetics, diffusion of the degree of cure, which depends on its value and the viscosity. All free surfaces (vacuum bag and open mold) are exposed to convective action of ambient air at a certain temperature. The model describes the whole complex of the listed phenomena up to the beginning of resin gelation, which prevents its movement in the preform.

The above phenomena are considered by a system of coupled governing equations, which includes:

\[ \frac{\partial \phi}{\partial t} + \mathbf{u} \cdot \nabla \phi = \nabla \cdot \gamma \mathbf{G} , \]

whose dependent variable \( \phi \in [-1;1] \) allows to define a local resin filling distribution according to the relationship \( V_r = (\phi + 1)/2 \in [0;1] \).
- the modified Richards equation [26], which represents the movement of water and pressure

\[ (1-V_f) \cdot \frac{2}{\pi} \cdot \frac{\zeta}{1+(\zeta p_m)^2} \cdot \frac{\partial p_m}{\partial t} - \nabla \left( \frac{[K]}{\mu} \cdot \nabla p_m \right) = 0; \]  

(2)

- the convection/diffusion/kinetic equation for the time-space evolution of degree of cure \( \alpha \). The accepted form of this equation combines three most important phenomena in the moving epoxy resin – diffusion of \( \alpha \) depended on the kinetic and rheological state of the resin [27] and its displacement during resin spreading [28]

\[ \frac{\partial \alpha}{\partial t} - \left( \frac{[K]}{\mu} \right) \cdot \nabla p \cdot \nabla \alpha - \nabla \cdot \left( c_{\alpha} \nabla \alpha \right) = F(\alpha, t, T); \]  

(3)

- the heat transfer equation

\[ \rho_{pr} C_{pr} \frac{\partial T}{\partial t} + \nabla \cdot \left( -k_{pr} \nabla T \right) = Q_{exo}, \]  

(4)

and corresponding boundary and initial conditions that are described in detail in [19].

In these equations (1) – (4) \( \gamma \) is the phase mobility, \( G \) is the chemical potential of two phases (resin and air interaction), \( u \) is the superficial resin velocity, \( V_f \) is a fiber volume fraction, \( [K] \) is a permeability tensor, \( \mu \) is resin viscosity, \( \zeta \) is the reciprocal of a certain reference pressure \( p \), taken equal to atmospheric one \( \zeta = 1/p_{atm} \). To take into account its dependence on the degree of cure and viscosity the diffusion coefficient \( c_{\alpha} \) in equation (3) is accepted in the form

\[ c_{\alpha} = c_{\alpha}^0 \cdot \frac{(1 + \tanh((\alpha - 1) \cdot \sigma_{\alpha}))}{(\max(\log(10(\mu)-1)+2) \cdot V_r),} \]  

(5)

where the values \( c_{\alpha}^0 = 0.001 \) and \( \sigma_{\alpha} = 0.15 \) were determined on the basis of the compared results of experiments and numerical simulations carried out using a simple1D system for a liquid composite molding. The thermal properties of the preform: mass density \( \rho_{pr} \), specific heat capacity \( C_{pr} \) and thermal conductivity \( k_{pr} \) are determined using mixing rule by using the same thermal properties of resin, dry preform and a local distribution of the resin filling \( V_r \) [29]. The intensity of the exothermal heat source is defined as

\[ Q_{exo} = Q_{tot} \cdot \rho_r \cdot (1-V_f) \cdot V_r \cdot \frac{\partial \alpha}{\partial t}, \]  

(6)

where \( Q_{tot} \) is the total amount of heat released during the curing of the unit mass of the resin and \( \rho_r \) is its mass density. To eliminate the discontinuity in the dependence of the resin viscosity on the degree of cure, which is inherent in all modifications of the Castro-Makosko model [30,31], which is extremely undesirable in numerical modeling, we have proposed a model similar to [32]

\[ \mu(T, \alpha, t) = \mu_0(T^{in}) \cdot \exp(v_1 \cdot (T(t) - T^{in}) + v_2 \cdot \alpha(T, T^{in}, t)), \]  

(7)

which has an additional advantage - it uses a directly measurable parameter - the viscosity at the initial temperature \( \mu_0(T^{in}) \) and coefficients \( v_1, v_2 \) determined from the results of the experiment.

The process model implemented in Comsol Multiphysics 5.5 provided the ability to track at each time step the volume averaged, maximum and minimum values of the degree of cure \( \alpha \), viscosity \( \mu \), temperature \( T \), internal \( p_m \) and compressive \( p_{comp} \) pressure, relative volumes filled with resin \( V_r \) and voids \( V_\phi \), fiber volume fraction \( V_f \) and other process characteristics.
3. Numerical simulation of vacuum infusion of a complex 3D part
As an object for testing the developed software tools, a three-dimensional composite structure with two cutouts and a high permeability medium (HPM) tape laid along the perimeter was chosen (see figure 1, a). A preform with a thickness of 3 mm, which was laid of 15 layers of carbon fabric, had omnidirectional in-plane permeability. The HPM was modeled with a 20-fold increase in permeability. The 5 mm thick mould was made of cured carbon fiber reinforced plastic (CFRP). After removing the joints of the surface patches and building the CAD model of the mold, the assembled preform and mold model was imported into the environment of the finite element package and meshed (see figure 1, b). Pre-performed simulations allowed the choice of the layout of the resin injection ports and vacuum vent, providing minimal complication of the pattern of the racetracking and mixing resin flows. Toray ER450 resin was injected into the preform at an initial temperature of 70 °C, and then the system was gradually heated by convective heat fluxes and kept under isothermal heating. In our numerical experiments, the isothermal holding temperature was varied in the range (80-88 °C), and the position of the vacuum port changed relative to a certain reper point on the lower boundary of the part, as shown in figure 2.

Some time dependences of the process parameters obtained during its simulation, when the shift (left) of the vacuum port was 40 mm, the width was 70 mm, and the gap between the HPM was 50 mm, are shown in figure 3. The time dependences of the minimum values of the preform filling with resin (see Fig. 3, a) demonstrate a sharp increase over a short time interval. During these time intervals, an increase in the resin viscosity occurs in the vicinity of the vacuum port, while the average resin viscosity over the preform begins to rise much later (see figure 3, b). This difference is quite natural, since the resin, coming to the outlet, moves along the preform at an elevated temperature for the longest time and, therefore, its degree of cure and viscosity are the highest.
Figure 3. Time histories of the minimum resin filling value $\text{Min}(V_r)$ (a), the average resin viscosity $<\mu>$ and the maximum resin viscosity around vacuum vent $\text{Max}(\mu_{\text{vent}})$ (b).

Figure 4. Two snapshots of the distribution of degree of cure $\alpha$ within the preform at the times when the resin fronts $V_r=0.1$ (a) and $V_r=0.9$ (b) leave the preform.

The duration of these onsets of minimum resin filling is very short, but in such a short time the value of $\text{min}(V_r)$ increases from 0.1 to 0.9. This situation is shown in figure 4, where the front $V_r = 0.1$ is colored green, $V_r = 0.5$ is yellow, and $V_r = 0.9$ is red. The corresponding time instants are hereinafter referred as $t_{01}$, $t_{05}$ and $t_{09}$. We investigated the possibility of early prediction of the results of the process, since the time interval between these moments and the moment $t_{\text{stop}}$ of the start of rapid gelation of the entire volume of the resin is very large. The results of this study showed that only the moment $t_{09}$ can be used for reliable prediction.

Most of the works devoted to optimizing the infusion process consider it as achieving a minimum volume of voids in the preform (quality criterion) [12,13,15,19,28,33] and / or minimizing the process duration (performance criterion) [3,34,35] until the filled preform has completely solidified. Some papers [14,16,17] also offer a multiobjective optimization technique. Usually, as the variable parameters of the optimized system the parameters of the ports layout and the temperature schedule are accepted.

Nevertheless, some authors [36, 37] believe that the post-infusion stage, which corresponds to the time interval after $t_{\text{stop}}$ and up to complete consolidation of the preform and determines the total process duration, should be considered separately for optimization. Obviously, this statement is true, since the states of the system components during the infusion and post-infusion stages are completely different. During the actual infusion, the system is described by the equations for the flow of a viscous fluid in a porous medium, and at the post-infusion stage, the system should be considered as a solid body with time-varying elastic-plastic properties and emerging residual stresses. To test the possibility of reducing the duration of the infusion stage of the process, a simulation cycle was performed with varying the process scheme and temperature regime. Some corresponding results in the form of stems diagrams for the durations of the times $t_{09}$ and $t_{\text{stop}}$ are shown in figure 5.
Figure 5. Dependencies of the process duration up to moments $t_{09}$ (left) and $t_{stop}$ (right) at isothermal holding temperatures of 80, 82, and 84 °C on the layout of the resin injection and vacuum ports

These diagrams clearly show the following patterns. With an increase in the heating temperature, the duration of the stage until $t_{09}$ is significantly reduced. Thus, for temperatures of 80, 82 and 84 °C, the ratio of durations to $t_{09}$ is approximately 1.5: 1.2: 1, respectively. However, the durations of the time intervals up to the time instants $t_{stop}$ are practically unchanged. This result confirms the conclusion of works [36, 37] that it is impossible to optimize the performance of the process taking into account its evolution only until the start of resin gelation. Obviously, it is necessary to consider the modes of the post-infusion process, which includes two- or more stages. This fact forced us to confine ourselves to considering the optimization of the quality of the infusion process.
4. The primary, the partial predictive and combined quality objectives at the vacuum infusion process optimization

In our study, the main quality indicator of the infusion process is the residual void volume in the preform at the onset of resin gelation \( t_{stop} \), which is quite consistent with most other works, e.g. [4-8, 19]. Figure 6 shows the response functions of the residual unfilled volume \( V_\phi \) at times \( t09 \) and \( t_{stop} \) on the parameters of the process layout, as well as as dot plots expressing the correlation between \( V_\phi \) \( (t09) \) and \( V_\phi \) \( (t_{stop}) \), for two temperatures 82 and 84 °C of isothermal holding of preforms. The relief of both response functions \( V_\phi \) \( (t09) \) and \( V_\phi \) \( (t_{stop}) \), especially for a temperature of 82 °C, is highly complex, but the behaviour of these functions is very similar. Moreover, scatter plots show strong correlation between them, which proves that it is possible to predict the value of the main quality criterion \( V_\phi \) \( (t_{stop}) \) on the base of the previously determined predictive criterion \( V_\phi \) \( (t09) \). However, the complex nature of the presented dependencies, caused by the confusing pattern of the resin flows, significantly degrades the reliability and stability of achieving the optimal quality of the process.

To identify other pre-estimated process parameters affecting its quality and referred hereafter as sub-objectives, we investigated the cross-correlation of the main quality criterion \( V_\phi \) \( (t_{stop}) \) with the average resin viscosity \( \mu(t09) \), the degree of its cure \( \alpha(t09) \), pressure in the filled part of the perform \( p_m(t09) \), with the maximum values of resin viscosity \( \max(\mu_{out}(t09)) \) and filling with resin \( \max(V_{r_{out}}(t09)) \) near the vacuum port, assessed at time \( t09 \). The results of this study demonstrated very weak cross-correlation of each pair of analyzed parameters and significant scattering of points on scatter plots of the type shown in figure 6. However, all of the listed sub-objectives have a similar relief of the response functions to the parameters of the process layout at all studied temperatures (see figure 7). Their hugely regular relief indicates the existence of areas within which there is a significant decrease, or even a minimum of these sub-objectives. It is important to note that although the values of these sub-objectives themselves are weakly correlated \( \text{corr} \approx (0.4...0.5) \) with the final quality criterion \( V_\phi \) \( (t_{stop}) \), their minimization is advantageous for higher resin flow rates after \( t09 \), i.e., contributes to the reliability and stability of reaching the minimum by the objective \( V_\phi \) \( (t_{stop}) \).

A significant difference in the nature of the influence of \( V_\phi \) \( (t09) \) and other above listed sub-objectives on \( V_\phi \) \( (t_{stop}) \) suggests the advisability of introducing a certain combined sub-objective, the use of which would allow predicting the optimal values of the parameters of the process layout, ensuring at the adopted temperature the minimum value of \( V_\phi \) \( (t_{stop}) \) reaching with maximum reliability. For its correct definition, an additional study of the mutual correlation of each pair of sub-criteria \( \langle \mu(t09) \rangle , \langle \mu(t09) \rangle , \langle p_m(t09) \rangle , \max(\mu_{out}(t09)) \) and \( \max(V_{r_{out}}(t09)) \) was carried out. Its results showed a very strong cross-correlation of all these sub-criteria, confirming that taking into account even one of them in the combined criterion is sufficient to characterize the process reliability. We propose a combined quality objective in the form of a product of the normalized partial predictive criteria, limited by some constraints, which depend on the specific process and resin requirements:

\[
\text{CombObj} = \frac{\langle V_\phi \rangle_{\text{mean}(V_\phi)} + \langle \mu \rangle_{\text{mean}(\mu)}}{\text{mean}(\langle V_\phi \rangle_{\text{mean}(V_\phi)} + \langle \mu \rangle_{\text{mean}(\mu)})_{t09}},
\]

(8)

where \( \text{mean}(\langle V_\phi \rangle) \) and \( \text{mean}(\langle \mu \rangle) \) are average values of residual air volume and resin viscosity, respectively, determined from the results of several process simulations at the varied conditions, whereas \( \langle V_\phi \rangle_{\text{lim}} \) and \( \langle \mu \rangle_{\text{lim}} \) are the maximum permissible values of these process parameters. The contour line plots for this combined process quality objective are shown in figure 8.
Figure 6. The response functions of the residual void volume $V_\phi$ in the preform at times $t_09$ and $t_{stop}$ on the parameters of the vacuum vent location and the correlation between these two volumes for the isothermal holding temperatures 82 (left) and 84°C (right).
Figure 7. The response functions and the contour plots of the predictive sub-objectives \( <\alpha(t09)> \) and \( <\mu(t09)> \) at 82 °C holding temperature

Figure 8. The contour plots of the predictive combined objective at the holding temperatures 82 °C (a) and 84 °C (b)

One can see that topology of the contour lines for the introduced combined quality objective defined by equation (8) is much simpler comparing to the contour lines of the main objective \( V_{\phi}(t_{\text{stop}}) \) in figure 6. In addition, the optimal areas appear more clearly, which contributes to a greater robustness of the optimization algorithm using such a combined objective. During about 100 simulations of the vacuum infusion process of the composite structure shown in figure 1, estimates of the reduction in simulation time to \( t09 \) were obtained. These results are presented as dependences on isothermal holding temperatures in figure 9.
These two dependences correspond to the minimum (red dotted line) and maximum (blue solid line) duration of the process simulation at each temperature. As can be seen in the plots, these dependences are of extreme nature, which is explained by the following factors. For all investigated temperatures (80...88 °C) the time integration step was set equal to 30 sec. In the lower part of this temperature range, the flow rate of the moving resin is relatively low and the duration of $t_{09}$ is long (see figure 5). At temperatures above 86 °C, the rate of resin flows, especially at the initial stage of infusion, is much higher, but due to the complex pattern of their spreading, the modeling algorithm is forced to split the time integration step. Therefore, despite the reduction in the duration of $t_{09}$, the duration of the simulation of the process up to this point increases. Further simulation of the process runs with a significant deceleration of the flows velocities, which does not require a decrease in the time integration step. However, as shown above, the duration of the process up to the moment $t_{stop}$ is practically independent of temperature. Therefore, there is a certain temperature range (in our case, 82...86 °C), in which the use of the predictive approach gives the greatest gain in simulation time.

5. Conclusions
The developed modeling tool provides a correct reconstruction of the vacuum infusion process dynamics, the resin flow front propagation, allowing identifying the unsaturated and void areas in the preform. Also, it procures the monitoring of local and averaged values of the process parameters within the preform during simulation. The article shows that it is impossible to evaluate the performance (full duration) of the vacuum infusion process at the stage of preform filling. For this, it is necessary to analyze the behavior of the cured composite structure at the subsequent, post-infusion stage of the process. An adequate predictive assessment of the quality of the process - the presence of possible dry spots and the relative unfilled void volume of the preform - can be performed at a point in time corresponding to the exit of the front of the resin filling $V_r = 0.9$ from the preform. To adapt the developed methods and software for modeling the vacuum infusion process in the production of composite structures, it is proposed to use a combined criterion, including predictive subcriteria for the quality of the process and its reliability. The proposed prognostic approach, implemented in the software module for solving the forward coupled problem of modeling the infusion process, provides a gain in simulation duration from 15 to 50%, which is of fundamental importance for the efficiency of the optimization system using such a module.

Acknowledgments
This work was supported by the Russian Academy of Science [project No. AAAA–A16-116012610052-3].

Figure 9. The dependencies of the computation time reduction due to the use of the predictive combined quality objective on the holding temperatures
References

[1] Heider D. and Gillespie J W 2010 Proc. FAA Jr. Adv. Mater. Struct. Cent. Excell. (Seattle, WA) p 12
[2] Hsiao K-T and Heider D 2012 Vacuum assisted resin transfer molding (VARTM) in polymer matrix composites Manufacturing techniques for polymer matrix composites (PMCs), ed S G Advani and K-T Hsiao (Cambridge, UK: Woodhead Pub Ltd), pp 310-347
[3] Garschke C, Weimer C, Parlevliet P P, and Fox B L 2012 Compos. Part A-Apppl. S. 43 (6) 935
[4] Rydarowski H and Mateusz K 2015 J. Compos. Mater. 49 (5), 573
[5] Bertling D, Kaps R and Mulugeta E 2016 CEAS Aeronaut. J. 7 577
[6] Fernlund G, Wells J, Fahrang L, Kay J and Poursartip A 2016 IOP Conf. Series: Materials Science and Engineering 139 012002
[7] Seong D G, Kim S, Lee D, Yi J W, Kim S W and Kim S Y 2018 Materials 11 (10) 2055
[8] Schechter S G K, Centea T and Nutt S R 2020 Compos. Part A-Apppl. S. 130 105723
[9] Brusche M V and Advani S G 1994 Int. J. Numer. Meth. Fl. 19 (7) 575
[10] Fracassi F T and Donadon M V 2018 J. Compos. Mater. 52 (27) 3759
[11] Lionetto F, Moscatello A, Totaro G, Raffone M, and Maffezzoli A 2020 Materials 13 (20) 4800
[12] Gokce A and Advani S G 2004 Compos. Part A-Apppl. S. 35 1419
[13] Hsiao K T, Devillard M and Advani S G 2004 Model. Simul. Mater. Sc. 12 (3) S175
[14] Ruiz E and Trochu F. 2006 Compos. Part A-Apppl. S. 37 (6) 913
[15] Dong C 2007 J. Compos. Mater. 41 (15) 1851
[16] Struzziero G and Skordos A A (2019) Advanced Manufacturing: Polymer & Composites Science 5 (1) 17
[17] Chai B X, Eisenbart B, Nikzad M, Fox B, Blythe A, Blanchard P and Dahl J 2021 Compos. Part A-Apppl. S. 149 106540
[18] Shevtsov S, Zhilyaev I, Chang S-H, Wu J-K, Huang J-P and Snezhina N 2020 Applied Sciences 10 (4) 1485
[19] Shevtsov S, Zhilyaev I, Chang S-H, Wu J-K, Huang J-P and Snezhina N 2021 Compos. Struct. 259 113437
[20] Shmueli G 2010 Stat. Sci. 25 (3) 289
[21] Yu L, Yang Z and Tang L 2016 Int. J. Inf. Tech. Decis. 15 (2) 423
[22] Katsonis P and Lichtarge O 2019 Hum. Mutat. 40 (9) 1436
[23] Seçkin M, Seçkin A Ç and Coşcun A 2019 J. Eng. Fiber Fabr. 14 1558925019883462
[24] Balcioglu H E and Seçkin A Ç 2020 Arch. Appl. Mech. 91 223
[25] Yue P, Zhou C, Feng J J, Ollivier-Gooch C F and Hu H H 2006 J. Comput. Phys. 219 47
[26] Van Genuchten M T 1980 Soil. Sci. Soc. Am. J. 44 (5). 892
[27] Khoun L, Centea T and Hubert P 2010 J. Compos. Mater. 44 1397
[28] Wei B-J, Chuang Y-C, Wang K-H and Yao Y 2016 Polymers 8 (9) 337
[29] Dong C 2008 Compos. Sci. Technol. 68 (9) 2125
[30] Matveev M Y, Belnoue J P-H, Nixon-Pearson O J, Ivanov D S, Long A C, Hallett S R and Jones I A 2019 Compos. Struct. 208, 23
[31] Lionetto F, Moscatello A, Totaro G, Raffone M and Maffezzoli A 2020 Materials 13 (21) 4800
[32] Lee W I, Loos A C and Springer G S 1982 J. Compos. Mater. 16 (6) 510
[33] Malheiro J M and Nunes J P 2021 Advances in Evolutionary and Deterministic Methods for Design, Optimization and Control in Engineering and Sciences (Springer, Cham) pp. 319-340
[34] Saad A, Echchelha A, Hattabi M, and El Ganaoui M 2012 J. Reinf. Plast. Comp. 31 (20) 1388
[35] Hwang S, Park S Y, Kwon G-C and Choi W J 2018 Int. J. Adv. Manuf. Tech. 99 2743
[36] Robinson M J and Kosmatka J B 2014 J. Compos. Mater. 48 (13) 1547
[37] Shin J H, Anders M, Kim D, Jin B C and Nutt S 2021 J. Compos. Mater. 55 (10) 1419