Materials Research Proceedings 28 (2023) 407-416 https://doi.org/10.21741/9781644902479-45

An Inverse method for determining fabric permeability in vacuum assisted resin infusion for composite parts forming

VOSNIAKOS George-Christopher[1,a *], DIMAKOPOULOS Panagiotis J.[1,b] and VASILEIOU Anastasia[2,c]

[1]National Technical University of Athens, School of Mechanical Engineering, Manufacturing Technology Laboratory, Heroon Politehniou 9, 15773 Athens, Greece

[2]The University of Manchester, Department of Mechanical, Aerospace & Civil Engineering, Dalton Nuclear Institute, Oxford Rd, Manchester M13 9PL, United Kingdom

[a]vosniak@central.ntua.gr, [b]pjdimako@gmail.com, [c]anastasia.vasileiou@manchester.ac.uk

Keywords: Composite Materials, Resin Infusion, Permeability, Genetic Algorithms

Abstract. Vacuum Assisted Resin Infusion (VARI) method employs a mould on top of which a number of fabric pieces are laid up and impregnated by resin drawn through vacuum. Simulation of VARI depends on the determination of fabric permeability. In this work, permeability value is selected from a set of discrete values by a genetic algorithm. An impregnation simulation model is run on Comsol^{TM} to compute the flow front propagation inside the fabric. The genetic algorithm compares the evolution (propagation) of the impregnation front, in a space and time dimension, with the corresponding result of one single actual impregnation experiment, obtained by machine vision. A simple part suffices for this experiment assuming homogenous fabric porosity. The computational cost of the method is low, making it superior to experimental determination of permeability on expensive custom-made devices.

Introduction

Industrial production of large batches of laminate, e.g. carbon or glass fibre, composite parts, of small to medium size and complex geometry is mostly conducted exploiting Resin Transfer Molding (RTM) using a heated mold pair arrangement. The resin along with the catalyst (hardener) is then injected into the mold through the inlet ports. After hardening, the part is separated from the mold. RTM imparts good dimensional accuracy and good surface quality to both sides of the part. Vacuum Assisted Resin Infusion (VARI) is a comparatively low-cost method that is able to produce small to large parts, its main characteristics being similar to those of RTM. However, instead of the metal top surface of the RTM mold, an elastic membrane is used. Moreover, VARI uses vacuum to draw the resin into the mold displacing the air it encounters and flowing towards the vacuum port(s). The mold is in contact with only one surface of the fabric, the other surface being of inferior surface finish.

Permeability of the fabric is an extremely important factor in VARI as it is directly related to the completion of the impregnation. Experimental and computational / numerical simulation methods or a combination have been used to determine it.

Experimental determination of permeability is based on monitoring the propagation of resin front by exploiting different sensors, such as pressure sensors [2], images of the evolution of the front through the fabric [3], custom designed dielectric sensors [4], optical fibers woven into the preformed material [5]. Both saturated and unsaturated flow tracking was reported in some of these works. Based on experimental data, neural networks have also been trained to predict permeability from input parameters (fabric type, porosity, input pressure) [6,7].

To calculate permeability numerical models based on the Stokes / Darcy equations are experimentally validated. The models express macro-scale phenomena using standard software such as Comsol^{TM} [8] or 2D schemes based on voxels or boundary elements [9,10]. Models at micro-scale [11] are inevitably of limited size. In macro-scale modeling the way in which the fabric is modeled is pivotal, e.g. using permeable and non-permeable yarns [12], incorporating stochastic fabric diversity [13].

Since the permeability of a fabric is not known a priori to use the corresponding value in the numerical model, several simulations are performed until the results match the experimental ones either following brute force [8,13] or within an optimization loop [14]. Another approach reported computes bulk permeability and saturation rate at mesoscale and introduces them to the macroscale simulation validated against experimental measurement in a 1D infusion test [15].

In a very comprehensive review on composite forming, benchmarking work on 1D and 2D permeability measurement is reviewed being expected to lead to a pertinent ISO standard [16]. However, it is also recognized that shear and compaction of preforms does alter permeability locally, which undermines to some extent the generality of the benchmarking concept.

In the present work, determination of the fabric permeability value is based on the comparison of experimental results and the numerical prediction of the propagation of the flow front, iteratively through a genetic algorithm. The difference of the two fronts at consecutive moments yields the evaluation of the corresponding permeability value tested. Due to its stochastic nature the approach is efficient requiring only one experiment on a simple shape recorded on camera.

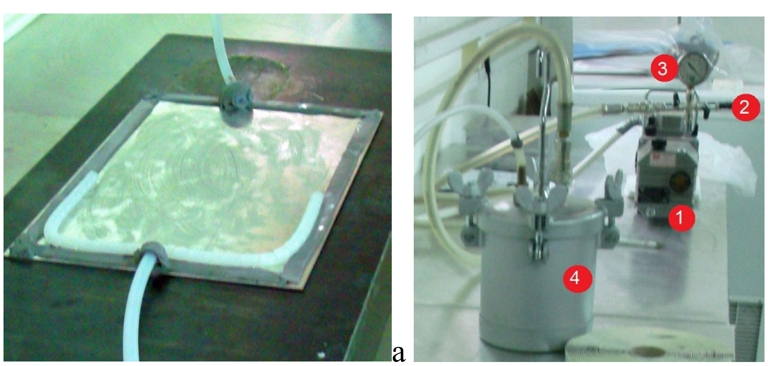
The next section describes the numerical modeling of the VARI process. Next is the description of the experiment providing the reference of the front evolution and in the next section the genetic algorithm that determines the optimal permeability for the specific fabric. Then, conclusions and suggestion of future work are drawn up.

Experimental Recording of Flow Front Evolution

A single VARI experiment suffices to provide a reference for the evolution of the flow front for comparison with the predicted evolution by the numerical simulation subsequently.

The specimen consists of two-ply glass fiber fabric measuring 200 X 75 mm with a nominal thickness of 0.02 mm per ply, plain weaving and weighing 25 gr / m^2. An appropriate peel ply was used with 0.15 mm thickness, a flow medium (mesh) with 1.2 mm thickness, a bottom bag (perforated) with 65 MPa strength and a vacuum bag (SBF 130B) with strength 45 MPa and thickness 0.075 mm. Entry and exit tubing had a diameter of 10 mm.

The resin was a 2-part Alphapoxy^{TM} HX-3 by Vivacity Engineering. Its viscosity at 25ºC is 325-375 mPa.s. Usage time at 25ºC is 45-60 min, full hardness being achieved after 24 hr. The mold was an aluminium plate of 1 mm thickness stiffened by ribs, see Fig. 1(a).



a b

Fig. 1. Experimental layout (a) mold with fabric, vacuum bag and in/out pipes (b) vacuum pump (1), regulating valves (2), manometer (3), resin trap (4).

Special sealing tape is employed to secure the vacuum bag on the mold. A two stage vacuum pump (DVP^{TM} RC.8D) is used with nominal pressure is 0.01 mbar and flow rate: 10.2 – 9.5 m^3/hr. A manometer of range – to -1 bar was used to measure the actual vacuum pressure achieved and a system of hand-regulated valves is used for controlling the vacuum circuit, which also comprises a downstream resin trapping vessel. The equipment is shown in Fig. 1(b).

The resin-saturated fabric is visibly darker than the unsaturated part, therefore the flow front is clearly delineated, see Fig. 2(a). In order to record the evolution of the front a 12 Mpixel CCD camera was used and 22 snapshots were taken at 1 sec intervals until the resin front reached the end of the fabric. Six tracks were defined about the axis of symmetry of the fabric parallel to it and the intersection points of the flow front with these tracks were recorded at each snapshot, see points A – F in Fig. 2(b). Their distance along flow direction (x axis) from the starting edge of the fabric was measured in pixels and scaled to mm. Thus, the mean distance of the six points defining each flow front was calculated representing a 'linearized' flow front,

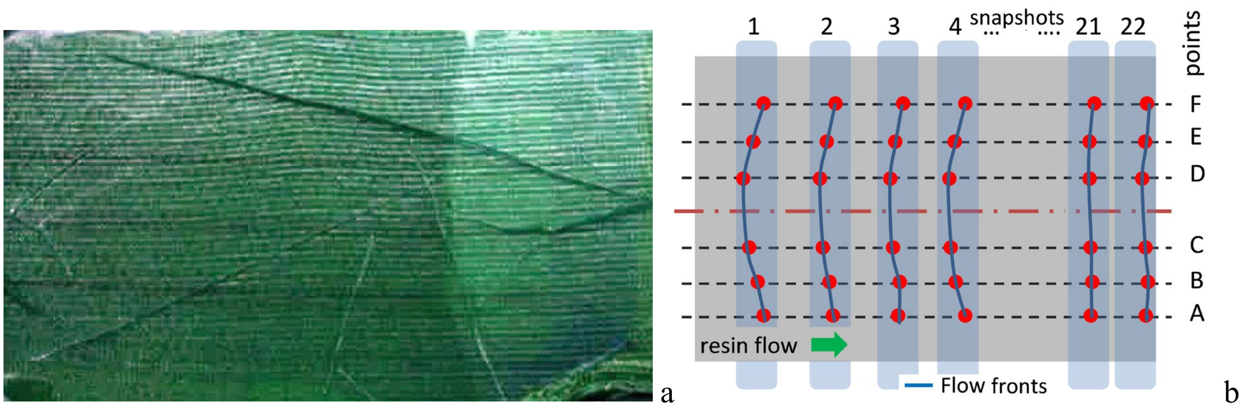


Fig. 2. Resin flow front (a) snapshot during the experiment (b) designated snapshots and points.

Numerical Simulation of VARI

Darcy's law governing one dimensional flow through porous media is expressed as:

$$v = \frac{k}{\mu}\frac{\partial^2 p}{\partial x^2} \tag{1}$$

v: resin velocity (m/s), k: fabric permeability (m^2), μ: resin viscosity (Pa·s), p: pressure (Pa).

Fabric filaments are bundled into tows which leave gaps between them as they are intertwined. These are visible as they are of the order of magnitude of mm (inter-tow gaps). Within a bundle gaps exist of 2-3 orders of magnitude smaller than those (intra-tow gaps). Resin flow between filaments of a bundle is modelled by a sink term describing resin flow around the gap. A corresponding expression for mass continuity is:

$$\nabla v = -S \tag{2}$$

where S is the sink term, its negative sign denoting that resin flow is reduced in the regions of non-saturated intra-tow gaps because it is absorbed by them.

Combining Darcy's law and continuity equation [28]:

$$v = -\frac{k}{\mu}\nabla(p) \tag{3}$$

$$\frac{\partial(\rho\varphi)}{\partial t} + \nabla(v\rho) = 0 \tag{4}$$

where φ is fabric porosity. Finally, using the sink term and assuming incompressible resin:

$$\varphi \frac{\partial S}{\partial t} - \nabla\left(\frac{k}{\mu}\nabla(p)\right) = 0 \tag{5}$$

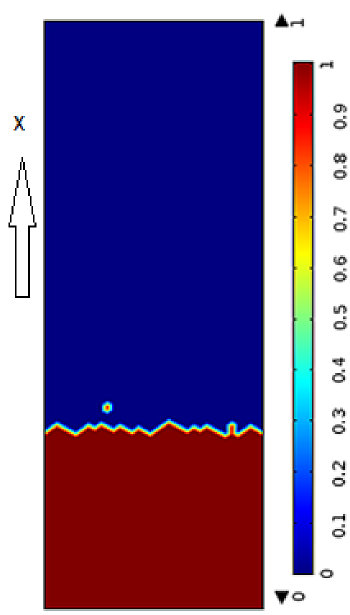
As the viscosity ratio of resin to air is quite high (10^4-10^6) zero pressure drop is assumed in the unsaturated section of the part and thus equal pressure on the flow front and the exit. Function S is defined to ensure smooth transition from a saturated to an unsaturated region [8]:

$$S(p) = \frac{2}{\pi}(ap) \rightarrow \frac{\partial S}{\partial t} = \frac{\partial S}{\partial p}\frac{\partial p}{\partial t} = \left(\frac{2}{\pi}\frac{\alpha}{1+(\alpha p)^2}\right)\frac{\partial p}{\partial t} \tag{6}$$

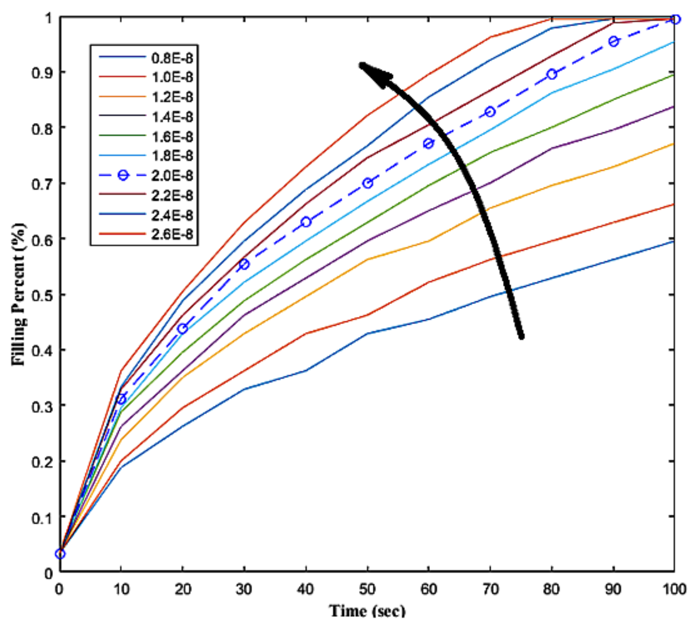
where $\partial S/\partial p$: moisture capacity and α: form factor [1/Pa] determining the length corresponding to phase change. [8].

The point at which the resin changes phase is determined by comparing the pressure resulting from Eq. 6 to the characteristic pressure at the flow front: $p > p_c a$. Normally, p_c = 1000 Pa [8].

The model was set up on Comsol™ concerning a fabric shaped as a parallelogram with resin flowing from one narrow end to the opposite along x direction, see Fig. 3(a).



a



b

Fig. 3. Simulation of resin infusion (a) flow front snapshot for t=30 sec, permeability 3.2e^{-12} m^2 and quadric fine mesh (b) evolution of filling percentage for different fabric permeability values.

The resin's change of viscosity with time was not modelled since it was considered fairly small (for AIRSTONE 710EL Epoxy Resin and 713H Hardener which is equivalent to the system used in the experiment, viscosity is reported by the manufacturer to be 150-200 mPa.s within the first 30 min, whereas impregnation time was a small fraction of 30 min in this case. Note that the fabric was modelled at single scale, i.e. ignoring the intra-tow gaps, which is knowingly a simplification at the same time allowing faster computation compared to dual scale modelling.

It is possible to record the flow front along a few lines parallel to the flow direction, interpolating between these points to draw up the complete flow front line, see Fig. 3(a). In addition, the filling percentage is used as a termination criterion for the simulation as calculated using the Derived Values>Average>line_Average method in COMSOL™. Fig. 3(b) shows the variation of filling percentage with time for various permeability values. It is clear that the higher the permeability, the earlier the filling ends, even before the front touches the fabric's right edge.

Materials Research Proceedings 28 (2023) 407-416 https://doi.org/10.21741/9781644902479-45

The density of the mesh can be set by the user as Extra Fine, Fine and Normal. In addition the discretization type of elements can be selected from the set: linear, quadratic, cubic, quatric, quintic, sextic and septic. Selection of different combinations impacts not only the accuracy of the flow front solution but also the actual position of the mesh nodes in the domain studies and hence the distance of the predicted flow front from the experimentally determined one. In particular, different combinations were tried for a simulation run for two layered GFRP fabrics at 0.8 bar vacuum and permeability 8.94 X 10^{-10} m^2. Concentrating on the experimental flow front position corresponding to the first snapshot recorded, which is located 10.52 mm downstream the entry baseline, Table 1 clearly shows superiority of combination Linear – Fine.

Table 1. Difference in predicted distance of the flow front from the baseline.

Density	**Extra Fine**		**Fine**		**Normal**	
Discretisation	Distance (mm)	Rel.error (%)	Distance (mm)	Rel,error (%)	Distanc e (mm)	Rel.error (%)
Linear	3,97	-62%	**10,53**	**0%**	12,96	23%
Quadratic	1,69	-84%	4,8	-54%	5,9	4,6
Cubic	2,74	-74%	6,85	-35%	8,43	2,07

Repeated execution of the simulation with different input values for permeability is implemented by corresponding calls from within a Matlab™ program by exploiting the Livelink™ application. Results are also transferred in the same way, in this case the flow front vector depicting its position at a predefined number of time points. Such repeated calls and passing back of the results are needed by the Genetic Algorithm described next.

Permeability Determination by Genetic Algorithm

The optimum value of permeability is the one that yields minimum deviation between the experimentally determined evolution of the flow front and the evolution predicted by the simulation model. This is determined by a Genetic Algorithm (GA) that uses the simulation model in order to evaluate the potential permeability solutions, see Fig. 4. The GA is based on the one reported on in [17].

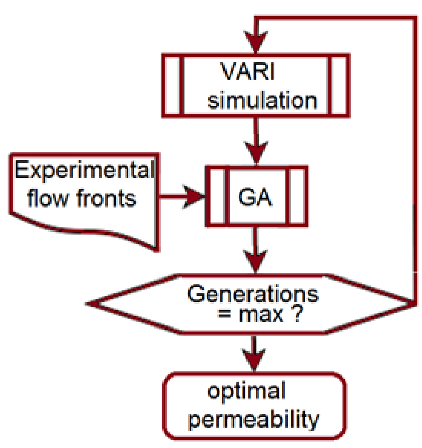


Fig. 4. Evolutionary determination of permeability overview.

The chromosome consists of an integer index to a set of 1000 permeability values spanning a user-defined range, in this case 3 X 10^{-9} to 9 X 10^{-10} (m^2). Thus the integer representation is decoded into a real representation.

Materials Research Proceedings 28 (2023) 407-416 https://doi.org/10.21741/9781644902479-45

The evaluation functions used is the Root Mean Square (RMS) of the difference of the x coordinate of the experimental (x_{e_i}) and the corresponding simulated (x_{s_i}) flow front considering all snapshots (T):

$$f_{eval} = \sqrt{\frac{\sum_{i=0}^{i=T}(x_{e_i}-x_{s_i})^2}{T}} \tag{7}$$

Note that the simulated flow front is by model construction a vertical line, whereas the experimental flow front can be considered as a circular arc with large radius that passes from the six 6 recorded points per snapshot, see Fig. 1(b). Thus, the experimental flow front is replaced by a vertical line passing from the mean x coordinate of these six points. The value of f_{eval} can be considered as a metric for the mean distance between the two flow fronts, measured and simulated one, over all snapshots considered. Normally all 22 snapshots taken should be taken into account, but it is up to the user to exclude any 'outlier' snapshots.

Since the chromosome is just one integer variable crossover operator would not keep any genes of the parent but the offspring would be an entirely new chromosome, which is exactly what mutation operator does in this case. Thus, crossover operator was abolished and only mutation was applied, indeed with a high probability of 40%. Elitism was constrained to 10%. Population consisted of 10 individuals and the initial population resulted from a random selection of 10 out of the 1000 permeability indices.

In order to validate the approach, the genetic algorithm was run first using instead of experimental flow front data the ones obtained by running the simulation model with a known permeability value, namely 3.7 X 10^{-9} m^2. In order to save computational cost only 10 snapshots were considered and the results are shown in Table 2. The cost was 0.554473 mm, which is deemed small enough to be accepted and the permeability determined was 3.71 X 10^{-9} m^2. The non-zero cost and associate small difference in predicted permeability is due to the discretization, i.e. the element nodes being inevitably some small distance apart from the actual flow front which is determined in the continuous domain rather than the discretized one.

Table 2. Difference between target and predicted flow fronts for the validation run.

snapshot number	1	2	3	4	5	6	7	8	9	10
time (sec)	0	2	4	6	8	10	12	14	16	18
target (mm)	9,55166	60,62378	85,18519	104,2885	119,29825	134,308	144,83431	158,8694	169,3957	178,9474
predicted (mm)	9,55165	60,62378	85,18518	104,2885	120,2729	134,308	146,39376	158,8694	169,3957	178,9474
relative error (%)	0,000001	0	0	0	-0,008170	0	-0,010767	0	0	0

The GA was then run with the actual experimental flow front evolution values for 500 generations. The evolution of the cost with the number of generations is shown in Fig. 5. The optimum permeability determined is 8.71 X 10^{-10} corresponding to a cost of 8435 μm.

Materials Research Proceedings 28 (2023) 407-416 https://doi.org/10.21741/9781644902479-45

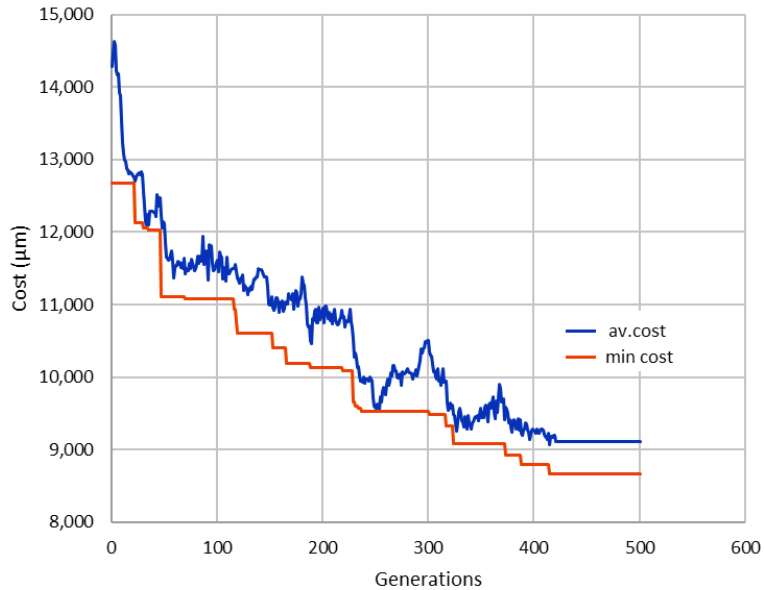


Fig. 5. Evolution of average and best (minimum cost) solution for the experiment conducted.

Characteristic snapshots of the experimental and the simulated flow front are shown in Fig. 6.

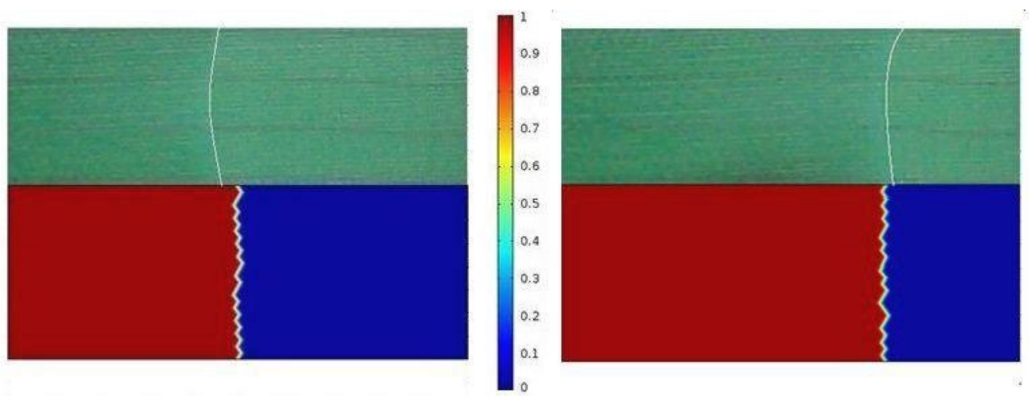


Fig. 6. Experimental (up) / simulated (down) flow front at 6 sec (left) and 12 sec (right).

A comparison between experimental and optimally predicted by the simulation flow front evolution in terms of their mean distance from the baseline is shown in Table 3 for a set of 11 snapshots for the 2-ply fabric. Furthermore, analogous experiments increasing the number of fabric plies to 3 and 4 was performed and the flow front evolution was measured as in the 2-ply experiment. The GA was run for these cases, too, resulting in lower overall permeability as well as higher impregnation time, namely 3,59 x 10^{-10} m^2 and 51 sec respectively for 3 plies and 1,07 x 10^{-10} m^2 and 117 sec respectively for 4 plies. This decrease in permeability with the increase of number of plies is reasonable and has also been reported in literature, e.g. [19]. The comparison between experimental and optimally predicted flow front evolution for the 3 ply fabric is also provided in Table 3.

Table 3. Difference between measured and predicted flow fronts for 2 and 3 ply cases.

plies	snapshot number	1	2	3	4	5	6	7	8	9	10	11
2	time (sec)	0	2	4	6	8	10	12	14	16	18	20
	target (mm)	10,5	42,5	72,5	97	114	134	146,5	159	172,5	185	192,5
	predicted (mm)	10,53	60,62	83,24	102,73	120,27	133,33	144,83	156,92	167,45	177,97	186,94
	relative error (%)	-0,29	-42,64	-14,81	-5,91	-5,50	0,50	1,14	1,31	2,93	3,80	2,89
3	time (sec)	0	5	10	15	20	25	30	35	40	45	50
	target (mm)	2,5	34	61,5	85,5	108,5	130	146,7	165	176	187,5	197
	predicted (mm)	2,74	59,99	82,97	102,18	117,83	132,81	144,81	156,59	168,6	180,02	189,62
	relative error (%)	-9,60	-76,44	-34,91	-19,51	-8,60	-2,16	1,29	5,10	4,20	3,99	3,75

Given that the simulation model is at single scale, i.e. approximate compared to a dual scale approach, the results are promising, namely the deviation of the experimentally determined and simulated flow fronts is mostly acceptable except for the snapshots corresponding to the first 20% of the experiment duration. The latter may, in addition to this simplification, be attributed to the effect of the vacuum bag compressing the fabric non-homogeneously, as also noted in [18].

On an Intel® Core™ i7-5500U computer 800 generations were run in about 80 min. The simulation run takes about 20 sec. Thus, an exhaustive search of 1000 permeability values would take by comparison 330 min.

Summary

The method advocated for determining permeability of fibre reinforced fabrics relies on simulation with a flow front evolution reference determined by a simple experiment on a simple fabric shape. By comparison, dedicated devices for determining permeability purely experimentally make use of special sensors and are expensive to make or acquire. Nevertheless, benchmarking has led to an ISO standard (ISO/DIS 4410). As far as this is still under development, visual tracking of the flow front coupled with numerical simulation in an optimisation loop may be a worthwhile addition to the sensor-based methods. In fact, there is plenty of scope in this direction since research on permeability evaluation in Liquid Composite Moulding (LCM) processes is an ongoing topic of research and of particular significance in process simulation [16].

The genetic algorithm as a tool for optimization coupled with a set of discrete values of permeability proved efficient, although it was, by definition, impossible to validate the result against experimentally measured permeability. Yet, the trend of permeability decreasing with increasing number of fabric pieces was clear and in accordance with results reported in literature.

The number and position of points to be considered on the flow front in the experimental setting and their simulation counterparts does influence the predicted permeability. This is connected to the fact that, for reasons of lowering computational cost, the fabric is modelled as single scale, i.e. ignoring the intra-tow gaps, that would otherwise have provided more accurate flow front shape. This is clearly an issue for further improvement.

The formulation of the genetic algorithm would most probably benefit from a binary representation of the integer indices to permeability. It is suggested that in the same range of values a finer step could be applied in this way and also that crossover operator could be meaningfully introduced in which case the number of generations to reach the optimum permeability would be slashed by at least one order of magnitude. This is the next step in further work, which will also allow inclusion of the type and density of finite element discretisation in the chromosome as two extra variables to be optimized. The chromosome could also be augmented by the critical pressure for phase change of the resin as a variable to be optimized, which has been taken as constant from literature (1000 Pa).

References

[1] A. Hindersmann, Confusion about infusion: An overview of infusion processes, Compos. Part A: Appl. Sci. Manuf. 126 (2019) 105583. https://doi.org/10.1016/j.compositesa.2019.105583
[2] C. Di Fratta, F. Klunker, P. Ermanni, Innovative approach to track flow front in LCM processes through pressure sensors in line quality control, 11th Intern. Conf. on Flow Processing in Composite Materials (FPCM 11), 2012, pp. 204-211.
[3] N. Vernet, E. Ruiz, S. Advani, J.B. Alms, M. Aubert, M. Barburski, B. Barari, J.M. Beraud, D.C. Berg, N. Correia, M. Danzi, T. Delaviere, M. Dickert, C. Di Fratta, A. Endruweit, P. Ermanni, G. Francucci, J.A. Gracia, A. George, C. Hahn, F. Klunker, S.V. Lomov, A. Long, B. Louis, J. Maldonado, R. Meier, V. Michaud, H. Perrin, K. Pillai, E. Rodriguez, F. Trochu, S. Verheyden, M. Wietgrefe, W. Xiong, S. Zaremba, G. Ziegmann, Experimental determination of the permeability of engineering textiles: Benchmark II, Compos. Part A: Appl. Sci. Manuf. 61 (2014) 172-184. https://doi.org/10.1016/j.compositesa.2014.02.010
[4] P. Carlone, G.S. Palazzo, Unsaturated and saturated flow front tracking in liquid composite molding processes using dielectric sensors, Appl. Compos. Mater. 22 (2015) 543-557. http://doi.org/10.1007/s10443-014-9422-3
[5] V. Antonucci, M. Esposito, M.R. Ricciardi, M. Raffone, M. Zarrelli, M. Giordano, Permeability characterization of stitched carbon fiber preforms by fiber optic sensors, Express Polym. Lett. 5 (2011) 1075–1084. http://doi.org/10.3144/expresspolymlett.2011.105
[6] S. Konstantopoulos, C. Hueber, E. Mühlbachler, R. Schledjewski, Identification of the effect of typical curvatures encountered in RTM parts on localized permeability of fibrous preforms, Adv. Manuf. Polym. Compos. Sci. 2 (2016) 57-66. https://doi.org/10.1080/20550340.2016.1229829
[7] H. Golestanian, M. Poursina, Neural Network Analysis Application To Permeability Determination of Fiberglass and Carbon Preforms, Chinese J. Polym. Sci. 27 (2009) 22-229.
[8] F. Klunker, S. Aranda, W. Surjoseputro, W. Wu, G. Ziegmann, C. Elsenhans, H. Behnke, Modelling the resin infusion process, Part I: Flow modelling and numerical investigation for constant geometries, Zeitschrift Kunststofftechnik/J. Plast. Technol. 7 (2011) 178-201.
[9] B. Verleye, S. Lomov, A. Long, D. Roose, C.C. Wong, Permeability of Textile Reinforcements : Efficient Prediction and Validation, Polymer. (2007) 2-3.
[10] X. Zeng, A. Endruweit, L.P. Brown, A.C. Long, Numerical prediction of in-plane permeability for multilayer woven fabrics with manufacture-induced deformation, Compos. Part A Appl. Sci. Manuf. 77 (2015) 266–274. https://doi.org/10.1016/j.compositesa.2015.03.027
[11] J.P. Dunkers, F.R. Phelan, C.G. Zimba, K.M. Flynn, D.P. Sanders, R.C. Peterson, R.S. Parnas, X. Li, J.G. Fujimoto, The prediction of permeability for an epoxy/E-glass composite using optical coherence tomographic images, Polym. Compos. 22 (2001) 803-814. http://doi.org/10.1002/pc.10582
[12] M. Griebel, M. Klitz, Homogenization and Numerical Simulation of Flow in Geometries with Textile Microstructures, SIAM Multiscale Model. Simul. 8 (2010) 1439-1460. http://dx.doi.org/10.1137/09077059X

[13] F. Zhang, B. Cosson, S. Comas-Cardona, C. Binetruy, Efficient stochastic simulation approach for RTM process with random fibrous permeability, Compos. Sci. Technol. 71 (2011) 1478-1485. https://doi.org/10.1016/j.compscitech.2011.06.006
[14] G. Morren, H. Sol, B. Verleye, S.V. Lomov, Permeability Identification of a Reference Specimen Using an Inverse Method, 2007 SEM Annu. Conf. Expo., 2007, 8.
[15] P. Carlone, F. Rubino, V. Paradiso, F. Tucci, Multi-scale modeling and online monitoring of resin flow through dual-scale textiles in liquid composite molding processes, Int J. Adv. Manuf. Techn. 96 (2018) 2215-2230. https://doi.org/10.1007/s00170-018-1703-9
[16] P. Boisse, R. Akkerman, P. Carlone, L. Kärger, S.V. Lomov, J.A. Sherwood, Advances in composite forming through 25 years of ESAFORM. Int. J. Mater. Form. 15 (2022) 1-30. http://doi.org/10.1007/s12289-022-01682-8
[17] A.N. Vasileiou, G.-C. Vosniakos, D.I. Pantelis, Determination of local heat transfer coefficients in precision castings by genetic optimisation aided by numerical simulation, Proc. Inst. Mech. Eng., Part C: J. Mech. Eng. Sci. 229 (2015) 735-750. https://doi.org/10.1177/0954406214539468
[18] L. Joubaud, F. Trochu, J. Le Corvec, Analysis of resin flow under flexible cover in Vacuum Assisted Resin Infusion (VARI), J. Adv. Mater. 37 (2005) 3-10.
[19] P. Mitschang, M. Glawe, D. Kreutz, G. Rieber, D. Becker, Influence of textile parameters on the through-the-thickness permeability of woven textiles, Proc. 11th Intern. Conf. on Flow Processing in Composite Materials (FPCM 11), 2012, 37-45.