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Data-Driven Identification of Composites Permeability from Flow Patterns

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Abstract — Fast, reliable and easy measurement of preform permeability is a crucial need for composite manufacturing by liquid molding. This paper proposes a data-driven method to identify permeability by tracking flow front information. We combine the data-driven computational mechanics scheme [6] along with the data-driven identification [8] and add necessary self-consistent corrections on the algorithms' parameters for the characterization of isotropic, orthotropic and general anisotropic permeability.
Keywords — Data-Driven Computational Mechanics, Permeability, Liquid Composite Molding

1. Introduction

Composites have become an essential part of today's materials in various industries, mainly due to their high mechanical properties such as strength to weight and stiffness to weight ratios, high corrosion resistance and fatigue life. With their prominent advantages over metals [9], composites have nevertheless some drawbacks and limitations in their use, i.e., fairly large processing and performance variabilities are induced by the uncontrolled microscopic changes in the composite part. With the permeability being one of the most sought parameters to be identified for composite processing, multiple approaches have been developed and are currently applied in the composites industry to determine the permeability of fibrous media. Yet, all methods and flow models used to simulate liquid injection molding and to determine the permeability values are based on the Darcy's linear equation [2] (Eq. 1).

$$<v_f> = -\frac{\overline{\overline{K}}}{\eta} . \nabla <P_f>^f \tag{1}$$

Where $<v_f>$ is the superficial Darcy's velocity, $\overline{\overline{K}}$ the permeability tensor, η the fluid viscosity and $<P_f>^f$ the fluid pressure.

The Darcy equation is based on many assumptions about the nature of interactions between the moving fluid and the fibrous medium viewed as a porous medium. However, there are many situations encountered in composite processes where these assumptions are not met. So this model is no longer valid and a new non-linear relationship between fluid velocity and pressure gradient must be determined for many cases.

Recently, Kirchdoerfer and Ortiz have introduced the concept of Data-Driven Computational Mechanics (DDCM in the following) [6], where constitutive equations are replaced by a database of measured stress-strain couples that samples the mechanical response of the material. Alternately, Leygue et al. [8] proposed a method that allowed the data-driven identification (DDI) of the material database: without introducing any modeling bias, DDI relaxes the necessity of an explicit or implicit strain-stress relation and identifies the material behavior by sampling the mechanical response.

The aim of the paper is to propose a data-driven methodology that allows the reliable identification of permeability using the least amount of experimental information; for this purpose, we choose to extend the scheme proposed by Leygue et al. [8]. The outline of the paper is as follows: first we briefly present classical methods that allow the permeability prediction. Then we recall the method from Kirchdoerfer and Ortiz [6] for data-driven simulation (DDS) and the one from Leygue et al. [8] for DDI, before extending it to the case of permeability identification from flow patterns.

2. Permeability

2.1. Definition

Primarily introduced by Darcy in 1856 [2] as an empirical geometrical property of the fibrous medium, permeability has become one of the most sought parameters to be identified, due to the huge expansion of the composites usage in high performance (aircraft, shipyard etc.) and high series (cars, sports and leisure etc.) industry. Permeability represents the ability of a medium to allow a fluid to pass through; a parameter that solely depends on the pore geometry of the porous medium. In the case of anisotropic medium, permeability is direction dependent, (fiber reinforced composites are a notable example of a porous medium with direction dependent properties) and can be written in the form of a symmetric second order positive definite tensor [1].

$$\mathrm{K}=\begin{bmatrix} K_{xx} & K_{xy} & K_{xz} \\ K_{xy} & K_{yy} & K_{yz} \\ K_{xz} & K_{yz} & K_{zz} \end{bmatrix}\ (m^2) \tag{2}$$

2.2. Classical measurement methods

Permeability measurement methods are classified based on the flow pattern: Unidirectional or 2D-Radial flow; the imposed boundary conditions: constant inlet pressure of fluid impregnating the bed, or constant flow rate; experiments can also be classified on whether the flow is in a saturated porous medium –or in a dry preform where the flow front is tracked. Multiple setups using radial flow method [4, 7, 10] or unidirectional flow method [5, 10, 11] were designed over the past thirty years. In parallel to these experimental setups, numerical techniques were developed to determine the permeability from experimental data (pressure, flow rate, flow front extent). (Fig. 1)

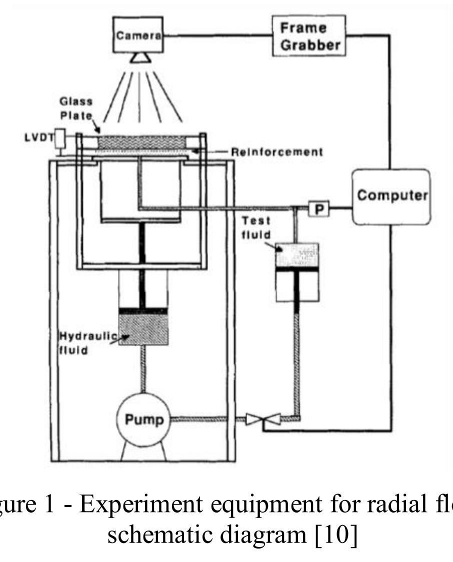

Figure 1 - Experiment equipment for radial flow - schematic diagram [10]

The above-mentioned methods and flow models are all based on Darcy's equation, which is a linear model. This bias was a major motivation for the introduction of a novel model-free approach based on the promising results of the DDCM paradigm in identifying material properties.

3. Data-Driven Computational Mechanics

DDCM introduces a new paradigm in computational mechanics in which fundamental balance principles and compatibility relations are enforced and where the numerical schemes used in their discretization such as finite elements, time-integrators, etc. remain unchanged. On the other hand, the stress-strain constitutive law classically formulated as $\sigma = f(\varepsilon)$ is replaced by a database of N^* admissible material states $(\varepsilon_i^*, \sigma_i^*)$, where $i = 1 \dots N^*$. Indeed, the constitutive relation and its parameters have an intrinsic phenomenological nature.

Considering a given material dataset measured from previous experiments, the data-driven solver seeks to assign to each element, "a prespecified data couple that is closest to satisfying the conservation laws. Equivalently, DD solvers aim to find the state satisfying the conservation laws that is closest to the data set." [6].

A priori, the problem is formulated as a minimization of a global weighted distance introduced in terms of two energies, $\boldsymbol{We}$ and $\boldsymbol{Ws}$ (3) as function of a parameter $[C]$, present in both energy forms, of numerical nature.

$$\boldsymbol{We}(\varepsilon) = \frac{1}{2}\, C\, \varepsilon^2 \qquad\qquad \boldsymbol{Ws}(\sigma) = \frac{1}{2\,C}\, \sigma^2 \tag{3}$$

Therefore, the objective function to minimize is:

$$arg \min_{\varepsilon_e,\, \varepsilon_e^*,\sigma_e,\sigma_e^*} \sum_e w_e\left(\boldsymbol{We}(\varepsilon_e - \varepsilon_e^*) + \boldsymbol{Ws}(\sigma_e - \sigma_e^*)\right) \tag{4}$$

Which is subject to the following constraints:

$$\begin{gathered} f_i = \sum w_e B_{ei} \sigma_e \\ \varepsilon_e = \sum B_{ei}\, u_i \\ \varepsilon_e^*, \sigma_e^* \in (\varepsilon^*, \sigma^*)_{N^*} \end{gathered} \tag{5}$$

Where i and e denote respectively the degrees of freedom and the indices over the quadrature points, w_e encodes the quadrature weight and B_{ei} the connectivity and geometry of the computational mesh.

The DDCM framework developed for small strain elasticity can be adapted to the flow in porous medium case in a straightforward manner through the following substitutions (Table 1).

Table 1 - Analogies between elastostatics and creeping flow in porous media

Discipline	Primary variable	Driving force	Flux	Conservation equation
Small strain elasticity	Displacement U	Displacement gradient ε	Momentum flux σ	$\nabla \cdot \sigma = f$
Flow in porous medium	Pressure P	Pressure gradient ∇P	Mass flux v	$\nabla \cdot v = 0$

4. Data-Driven Identification

In recent publications, Leygue et al. [8] proposed a method to find the material behavior in form of database of compatible states based on the concept of DDCM [6]. The method requires the displacement fields (pressure fields in our case) and the boundary conditions from multiple snapshots for solving the inverse problem: a minimization of the following objective function.

$$arg \quad \min_{\varepsilon_e^*, \sigma_e, \sigma_e^*} \sum_e w_e(\boldsymbol{We}(\varepsilon_e - \varepsilon_e^*) + \boldsymbol{Ws}(\sigma_e - \sigma_e^*)) \quad \textbf{(6)}$$

Thus, the algorithm identifies the material database of N^* compatible states $(\varepsilon_i^*, \sigma_i^*)$ and the stress field σ_e in the computational mesh simultaneously.

4.1. Data-Driven Permeability Identification Procedure

The porous geometry of trapezoidal shape with impermeable circular zones in the domain is created (Fig. 3). The preform has a fiber volume fraction of 50% and $K = \begin{bmatrix} 0.1 & 0.0 \\ 0.0 & 0.5 \end{bmatrix} m^2$ permeability. Impermeable zones force the fluid to flow around these obstacles, creating more geometrically complex flows. These latter reveal more local characteristics of the porous medium than a simple frontal flow [3].

Resin of 0.2 Pa. s viscosity is injected inside the medium via an inlet point at pressure P_{in}. The vent, at P_{out}, is situated at the opposite corner. Information on the flow front position and velocity at different time steps can be acquired – either numerically or via Digital Image Correlation technique in experiments.

4.2. Data-Driven Permeability Identification: Idealized Case

First, we set ourselves in an idealized case for DDI. Knowing the boundary conditions, we then acquire the full pressure field on each snapshot from computer simulations of the liquid injection process. This scheme allowed the data-driven identification of isotropic, orthotropic and general anisotropic permeability.

For the orthotropic permeability case, 8 different injection scenarios including different boundary conditions and inlet gate positions are designed. $N^* = 1000$ points were chosen to be identified for sampling the material response of the flow inside porous medium. The mismatch parameter $[C]$ is set to identity tensor. The database convergence (Fig. 2) is achieved within the first 21 iterations with a global error of 1.7%. The distribution of relative errors is shown in the histogram in Figure 2.

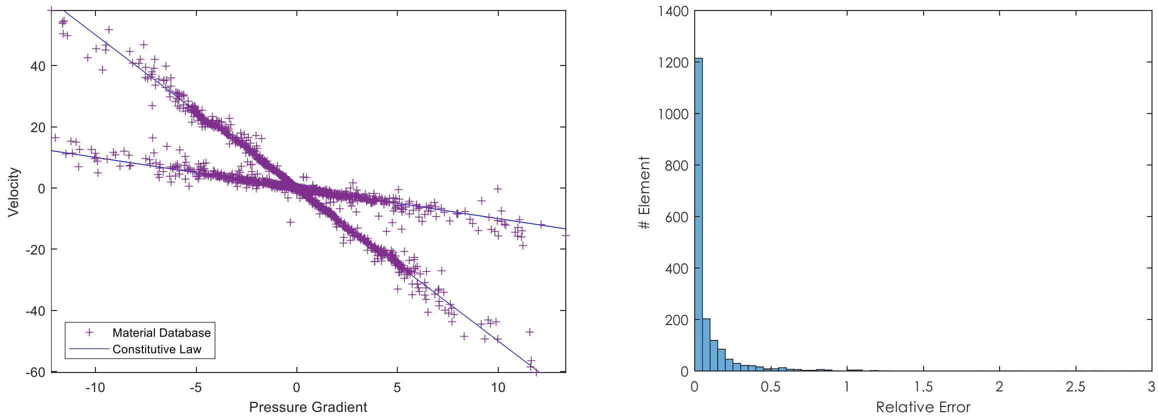

Figure 2 - Material Database Identified for Anisotropic Permeability (Left)
Histogram of Distribution of Relative Error (Right)

4.3. Data-Driven Permeability Identification: Realistic Case

From the experimental point of view, measuring the full pressure field in the mold represents a big challenge. Accordingly, we propose a data-driven method that replaces the unavailable pressure data required for DDI, by simulating the pressure field via DDCM with the current material database. The high dependency of this method on the mismatch parameter $[C]$ required the correction of the latter after each simulation until stagnation.

This identification process combining the DDCM and the DDI schemes was only possible if redundant information on the flow front were known: the flow front position and the velocity at different time steps of the injection.

The overall algorithm of the data-driven identification from flow patterns becomes as follows:

i. Input Guessed Material Database
ii. Run Data-Driven Simulation
iii. Compute Updated Material Database
iv. Correct [C]
v. Repeat steps ii - iv until convergence
vi.

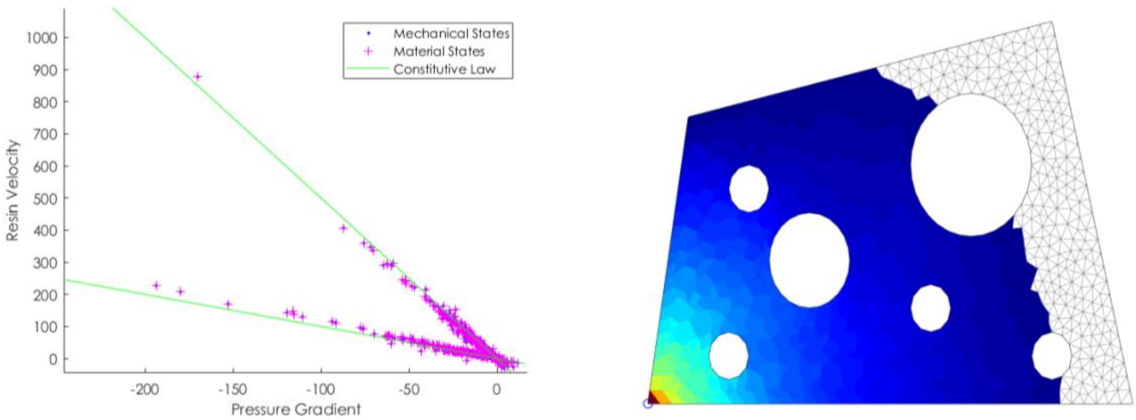

Figure 3 - Material Database Identified for Anisotropic Permeability from flow front information

Data from 20 snapshots of a single point injection experiment were gathered, N* = 1500 material states were chosen to be identified for sampling the material response for the flow inside the porous medium. The mismatch parameter [C], first set to identity tensor, is then updated by self-consistent corrections after each iteration. Starting with a database of zeros, the convergence was achieved within the first 4 iterations, and the global error dropped from 17% to 1% only after the first correction (Fig. 3).

5. Conclusion

The data-driven permeability characterization method based on the methodology originally developed for mechanics of materials brings multiple advantages with respect to current permeability identification techniques:

- No specific mathematical flow model has been used to back calculate the material property that links the flow velocity field to the pressure field. This method generalizes the classical permeability identification procedure to more complex cases where the velocity/pressure relationship is actually non-linear, making thus the solution uncertainty-free and inherited from accurately measured experimental data.

• Fluid viscosity and boundary conditions introduce no variabilities in the permeability determination.
• A minimum amount of data is required for the determination of isotropic and anisotropic permeability, by tracking flow front patterns in the domain at different time steps.

In addition, this data-driven identification method from flow patterns suggests an improvement over DDI as proposed by Leygue et al. by extending its capabilities [8]. Indeed, the full field data is not required for identifying material properties, instead, the missing information are self-constructed within the iterations.

6. Perspectives

For a formed fibrous reinforcement, local variations in fiber content and orientation exist, leading thus to spatial permeability variations. The proposed data-driven identification method will be extended to address 3D preforms to identify the local changes in permeability induced by the forming of fabrics.

As a continuation of this project, additional research will develop a low-cost, model-free, uncertainty-free identification method that can be implemented in various engineering problems.

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