Towards a manifold learning in parametric RTM processes. A geometric approach.

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Abstract. This work aims at providing a parametric solution of LCM processes, and in particular RTM, when the location of the injection gate is assumed being problem parameter. It is well known that parameters can be easily considered as model extra-coordinates within the Proper Generalized decomposition framework. Then, the use of separated representations allows efficiently circumventing the curse of dimensionality, and then calculating very efficiently the so-called computational vademecums that contain all the solutions of the problem at hand for any choice of the material, process or geometrical parameters. The interested reader can refer to the reviews [2, 3, 4, 5, 6] and the numerous references therein. However, even if the construction of such parametric solutions within the PGD rationale is nowadays in most of cases mature, using both intrusive [6] or non-intrusive [1] approaches, the last approach induces spurious solutions when interpolating solutions exhibiting localization. The present paper shows a parametric geometric approach for RTM processes where the injection gate is a parameter. It allows to move the inlet in real-time and to determine the effect that the inlet position has in the filling process. At the end of the papers, some numerical examples are shown.

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