A Cyber Physical System Approach For Composite Part: From Smart Manufacturing To Predictive Maintenance

Giacomo Quaranta[1,a),b)], Emmanuelle Abisset-Chavanne[2,a),c)], Francisco Chinesta[2,d)] and Jean-Louis Duval[3,e)]

[1]*ESI Chair @ Ecole Centrale de Nantes, 1 rue de la No, 44300 Nantes, France.*
[2]*PIMM, ENSAM ParisTech, 151 boulevard de lhpital, 75013 Paris, France.*
[3]*ESI group, 99 Rue des Solets, 94150 Rungis Complexe.*

[a)]Corresponding author: Emmanuelle.Abisset-Chavanne@ec-nantes.fr
[b)]URL: Giacomo.Quaranta@eleves.ec-nantes.fr
[c)]URL: Emmanuelle.Abisset-Chavanne@ec-nantes.fr
[d)]URL: Francisco.Chinesta@ec-nantes.fr
[e)]URL: Roland.Keunings@uclouvain.be

Abstract. In this work, a Cyber Physical System called Hybrid Twin is proposed for composite parts manufactured from RTM. This allows to introduce in the virtual twin of the parts the defect and the final properties induced by the real manufacturing process and to use on line data collection for predictive maintenance.

INTRODUCTION

Manufacturing of large composites parts usually involves long processes that proceed by injecting a resin into a mould occupied by a reinforcement perform. The associated forming process simulation, used to optimize and control the process, generally differs from the reality because of the important variability in the input matter material parameters in both space and time that is not (or badly) taken into account. Therefore, in order to be able to control the process and insure high quality part forming, the manufacturing system (namely the injection process) must adapt in real time to these changing conditions in the input matter characteristic but also to any change in the factory and even in the customer needs.

A key technology to reach this goal is the Cyber-Physical System (CPS) defined as a system of collaborating computational entities in intensive connection with the surrounding physical world, and in close relationship with such technologies as cloud, IoT and big data. In this context, we develop a CPS called Hybrid-Twin, that allows to i) predict the evolution of any dynamical system by exploring its entire possible state space (direct approach), ii) assimilate the data collected and adapt the dynamical system predictions to the real conditions (data assimilation and model evolution) and iii) build the dynamical systems that allow to reach the final needs (inverse conception).

In this work, this concept, and in particular the second ability of it (data assimilation and dynamical model correction), is applied to composite parts manufactured from RTM process. During the forming process, the Hybrid Twin is used to insure correct numerical prediction for control purpose and for introducing in the part life cycle prediction the accurate forming process information in order to allow the predictive maintenance. Another application of this CPS (not considered here) would be the use of the Hybrid Twin for the in service life of the part. Indeed, once the part is manufactured and in-service, it will be subjected to fatigue and impacts (e.g. tool fall, rain drops,), both them originating erosion or internal and external damage. In this context, the Hybrid Twin can be used for continuous monitoring allowing non-destructive testing, damage evaluation, and the anticipation of actions like maintenance and reparation.

In the first part, the concept of Hybrid Twin is presented and in particular its two main components: the parametric physically-based model (whose parameters will be updated on the fly from measurements) and the correction model constructed on-the-fly exclusively from the collected data. In the Second Part, the Hybrid Twin associated to the Resin Transfer Molding (RTM) process is detailed. The third part gives conclusions and perspectives.

HYBRID TWIN IN A SINGLE EQUATION

A given physical system state can be characterized by a number of discrete variables $\mathbf{X}$. Depending on the physics, $\mathbf{X}$ can contain temperature, velocities, stresses, viscosity... The system evolution is then described by the evolution of $\mathbf{X}$ from the initial state $\mathbf{X}_0$ at time t_0 to the current state $\mathbf{X}(t)$ at time t. In the numerical simulation, this current state is predicted by integrating the rate of change $\dot{\mathbf{X}}(\tau)$, $\tau \in (0; t[$.

When the physics governing the physical system state evolution is well known and established, the rate of change $\dot{\mathbf{X}}(t)$ can be expressed as $\dot{\mathbf{X}}(t, \mu)) = \mathbf{A}(\mathbf{X}, t; \mu)$, where μ represents the set of parameters involved in the model and that have to be identified offline or online. Moreover, in the context of process or system control, external actions are applied for driving the model solution towards the given target. Thus, the state rate of change (when ignoring noise) can be decomposed into two contributions: $\dot{\mathbf{X}}(t, \mu)) = \mathbf{A}(\mathbf{X}, t; \mu) + \mathbf{C}(t)$. The issues related to the parametric nature of the model and the real-time constrain for control can be solved by using model order reduction technics, in particular the Proper Generalized Decomposition [1, 2, 3, 4, 5].

$\mathbf{A}$ and $\mathbf{C}$ constitute the usual contributions of the numerical models used nowadays to predict and control process and system evolution. However, a non-negligible deviation is often noticed between the simulation predictions and the real evolution acquired from collected data. The unbiased deviation contribution is associated to modeling or measurement noise and is easily addressed by using adequate filters [6]. However, biased deviations express hidden physics and required a particular treatment. It is proposed to introduce in the system evolution a data-based deviation model build on-the-fly, directly from the collected data using i. e. machine learning technics (data-mining, deep-learning, manifold learning, ... for citing few) [7, 8, 9]. That allow then to write the fundamental equation of an Hybrid Twin:

$$\dot{\mathbf{X}}(t, \mu)) = \mathbf{A}(\mathbf{X}, t; \mu) + \mathbf{B}(\mathbf{X}, t) + \mathbf{C}(t) + \mathbf{R}(t) \tag{1}$$

expressing that the rate of change of the system state at time contains four main contributions:

- (i) the pre-assumed physical contribution whose state rate of change related to the model parameters reads $\mathbf{A}(\mathbf{X}, t; \mu)$;
- (ii) a data-based model $\mathbf{B}(\mathbf{X}, t)$ modeling the noticed gaps between prediction and measurement;
- (iii) external actions $\mathbf{C}(t)$ introduced into the system dynamics in order to drive the model solution towards the desired target;
- (iv) the unbiased noise $\mathbf{R}(t)$ that was traditionally addressed using appropriate filters.

RESIN TRANSFER MOLDING HYBRID TWIN

The problem consists in filling a square mold from its central point. An impermeable square insert is placed in the right-upper zone in order to break the solution symmetry. The experimental device is depicted in Fig. 1. In what follows, the construction and the use of the two first contributions of the hybrid twin - the physical () and the data-based () models - is described.

First, the parametric solution of the flow problem related to the mold filling process is computed offline. The chosen parameter is the preform permeability, that, without loss of generality, is assumed constant and isotropic in the whole preform. The parametric solution is constructed by coupling PAM-RTM and a non-intrusive formulation of the PGD constructor based on the sparse subspace learning, referred in the sequel as SSL-PGD. Then, as soon as this parametric solution has been computed offline, it can be particularized online almost in real-time, that is, all the fields (pressure, velocity, filling factor, ...) are accessible for any possible value of the permeability. Figure 2 depicts the flow front at different instants and for three different permeabilities. Then, by comparing the real flow front (recorded with a camera) with the just computed parametric solution, the effective permeability of the fibrous preform can be identified. Classical inverse methods just as the Levenberg-Marquard one can be used to achieve this identification. As soon as the permeability has been properly identified, and in absence of any perturbation, the simulated filling process agrees in minute to the one experimentally observed, as shown on the Fig. 3.

In the previous process stage, the permeability has been successfully identified using the first images recorded by the camera. However, the simulations used to build the parametric contribution assumes a homogeneous permeability

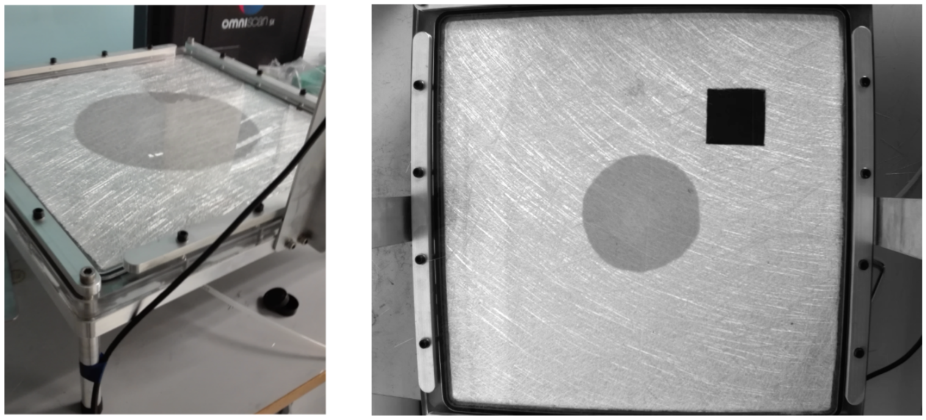


FIGURE 1. Experimental set up. The square mold is filled with an isotropic fibrous reinforcement and an impermeable square insert (black small square in the upper left corner.

repartition in the whole preform. Then, if a variation of permeability appears (for example in the neighborhood of the mold boundary due to the clamping system), the simulation performed with and the just identified permeability will significantly deviates from the measurement when flow reaches the regions where the permeability is reduced. Figure 3 compares the predicted solution with the one associated to the perturbed case. It can be noticed that, at the beginning, predictions are in perfect agreement with measurements, but when the flow reaches the region with lower permeability, significant deviations occur.

To tackle this issue, the data-based () model is introduced and constructed using, in this example, dictionary learning. To do so, a rich handbook of snapshots is produced, called the dictionary. Then the identified deviation, namely the difference between the real flow front position and the one predicted by , is projected on this dictionary under the constrain of increasing the sparsity of the resulting projection. In the present case, as the dictionary contains elements able to described the noticed flow behavior, the deviation can be perfectly represented by the data-based contribution (,), as illustrated in Fig. 4, ensuring the model predictability all along the filling process.

CONCLUSION

In this work, a CPS called Hybrid Twin has been proposed and applied to composite manufacturing. It is composed of four fundamental elements: (1) a physically based model compressed as parametric solutions in order to achieve real time parameters identification, (2) a dynamical correction constituted of a data-based model built on the fly from the collected data, that allow to fill the gap between the simulations and the observations, (3) a control term able to lead the solution toward the final target and (4) noise filters.

This Hybrid Twin has then been applied to RTM process. The parametric solution, build from PAM RTM commercial code, is there used to identify, from the first images of the measured flow front position, the preform permeability. The data-driven correction is then activated in order to take into account in the simulation the physics that occurs during the process but that have not been taken into account in the simulations, such as here, the permeability variation due to the clamping system.

This application of an Hybrid Twin for manufacturing process shows the efficient of such a concept in order to correct the physical model based simulations and allow then to predict accurately the manufactured part final properties. This final part state is a key information for the in-service behavior of the part and for the predictive maintenance system. The use of the collected data during the process allow a patient specific simulation and accurate prediction of such state to be injected then for example in the aging simulation. Finally, such a CPS concept can also be extended to the in-service life of the product in order to correct the aging model to the observed one and then to adapt the predictive maintenance cycle.

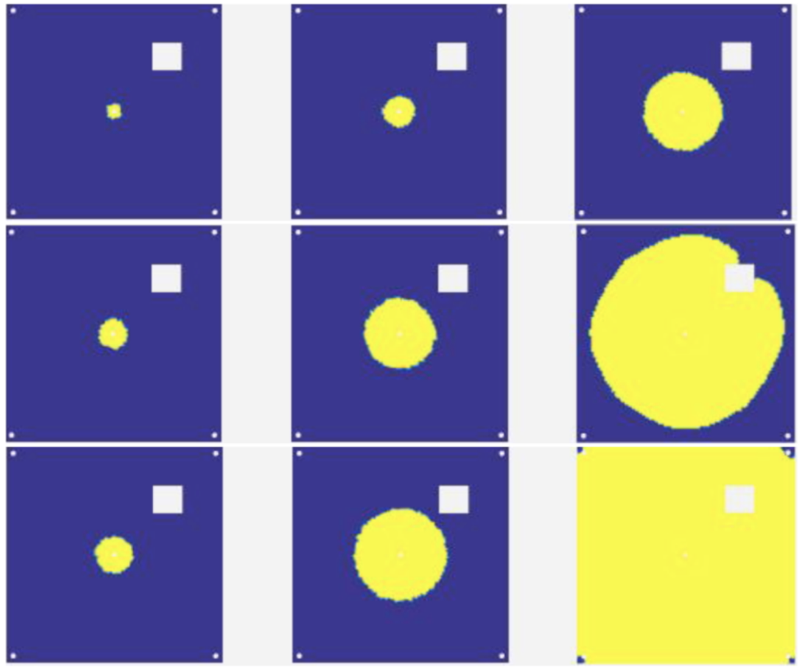


FIGURE 2. Particularizing the PGD-based mold filling solution for three different permeabilities (low at the left, intermediate at the center and high at the right) at three different time steps (from top to bottom).

REFERENCES

[1] A. Ammar, B. Mokdad, F. Chinesta, and R. Keunings, J. Non-Newton. Fluid Mech. **139**, 153–176 (2006).

[2] A. Ammar, B. Mokdad, F. Chinesta, and R. Keunings, J. Non-Newton. Fluid Mech. **144**, 98–121 (2007).

[3] F. Chinesta, P. Ladeveze, and E. Cueto, Arch. Comput. Methods Eng. **18**, 395–404 (2011).

[4] F. Chinesta, A. Leygue, F. Bordeu, J. Aguado, E. Cueto, D. Gonzalez, I. Alfaro, A. Ammar, and A. Huerta, Arch. Comput. Methods Eng. **20**, 31–59 (2013).

[5] F. Chinesta, R. Keunings, and A. Leygue, *The Proper Generalized Decomposition for Advanced Numerical Simulations* (Springerbriefs, Springer., 2014).

[6] D. Gonzalez, A. Badias, I. Alfaro, F. Chinesta, and E. Cueto, Comput. Methods Appl. Mech. Eng. **326**, 679–693 (2017).

[7] S. Brunton, J. Proctor, and N. Kut, PNAS **113**, 3932–3937 (2016).

[8] J. Kutz, *Data-driven modeling and scientific computation. Methods for complex systems and big-data.*

[9] R. Ibanez, E. Abisset-Chavanne, J. Aguago, D. Gonzalez, E. Cueto, and F. Chinesta, Arch. Comput. Methods Eng. **25**, 47–57 (2018).

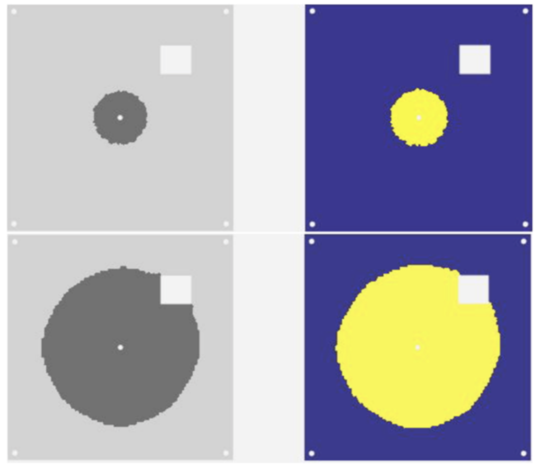
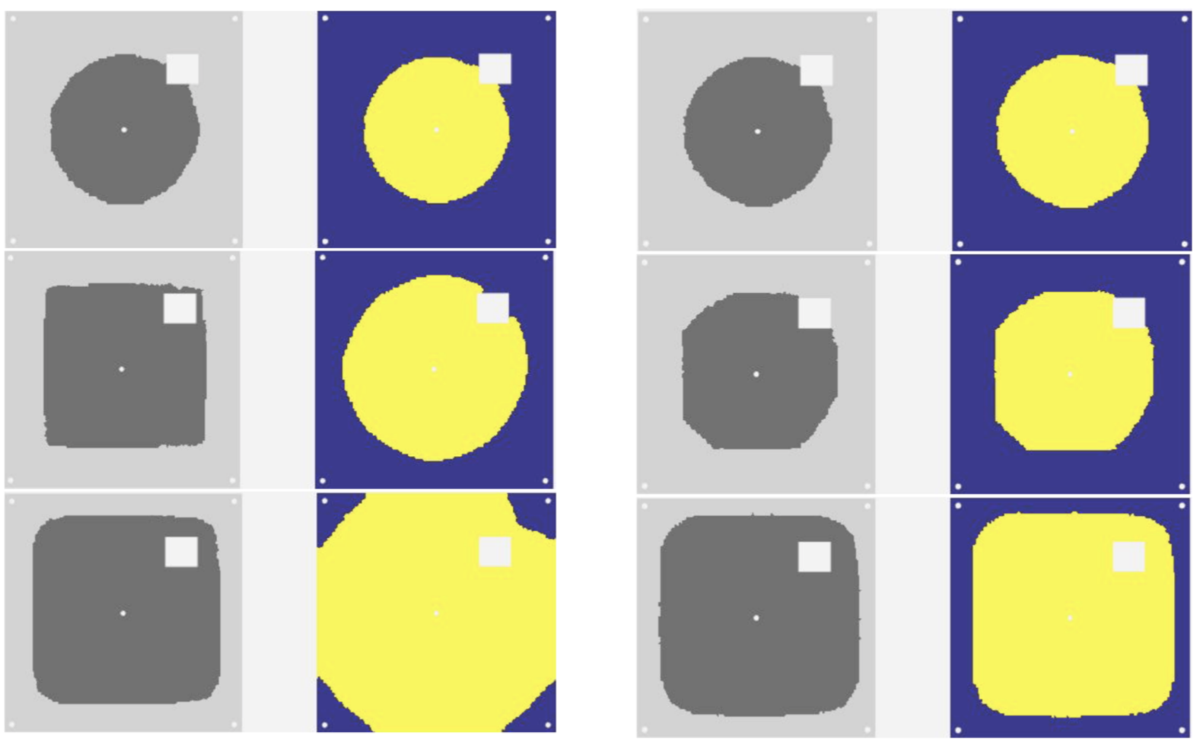


FIGURE 3. Identifying the fibrous reinforcement permeability and comparing measured (left) and predicted (right) flow front position at two time instants.



(a) (b)

FIGURE 4. Introducing a permeability reduction in the neighborhood of the mold boundary and comparing measured (left) and predicted (right) flow front position at three time instants (top to bottom): (a) without introducing the data-based model contribution and (b) introducing the data-based model contribution.