

COST 526 – Project F2

Final Report

Form Final properties of Components to Mould and process Design in Metal Injection Moulding

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1 Introduction

The metal injection molding process is an attractive technology for manufacturing in large batch small and complex metallic. The process consists of four steps: mixture and compounding of the binder and powder particles, injection molding, debinding and then densification. The compound is characterized by a high powder loading in the powder/binder mixture. The densification by solid state sintering should be accurately controlled to obtain the required geometry with an homogeneous microstructure for high performance applications.

The optimization of MIM process will be held in three stages. At beginning, it is necessary to control the segregation defect, and then identify the sintering models starting experimental tests, in order to simulate the sintering phase using these parameters identified thus the powders distribution optimized. Once the shrinkage is controlled, an algorithm of form optimization will be defined to manage the optimizer of each phases.

2 Optimization of injection phase

2.1 Cost function

Segregation is one of the major defects arising in metal injection molding. In order to optimize it, a cost function is defined to describe it as:

$$\left\{ \begin{array}{l} \min_x F(x) = \left(\frac{1}{N} \sum_{i=1}^N \frac{|\Phi_{S,i}(x) - \Phi_{S_0}|}{\Phi_{S_0}} \right) \\ (x_{i \min} \leq x_i \leq x_{i \max})_{i=1,\dots,4} \end{array} \right. \quad (1)$$

where Φ_{S_0} is the powder volume fraction, N is the total nodes number in the FE mesh, Φ_{S_i} is the powder volume fraction at the i th node, and $x = (x_i)_{i=1,\dots,4}$ is the process parameters vector which listed in Table 1. So the optimization problem is formulated as a minimization one as following:

Table 1: Process parameters vector in MIM

Vector x	Parameters	Range
x_1	Powder volume fraction	[0.4 – 0.7]
x_2	Interaction coefficient	[0.001 – 0.007 Pa.s.m-2]
x_3	Powder density	[1 – 8 g/cm3]
x_4	Binder density	[0.5 – 2.5g/cm3]

2.2 Proposed optimization strategy

The cost function is obtained through FE simulation of the MIM process. The application of a standard optimization methodology based on a genetic algorithm could be very time consuming, because it normally necessitates evaluating 2000 times or more the cost function. This remark has led the authors to develop a new optimization method which can reduce the computational time, using an adaptive response surface modeling.

In this approach [3], it is necessary to build parametric space equal to the parameters number, to discretize this space and to solve the matrix system associated. However, one always starts with an initial weak discretization with only three points per direction, corresponding to a restricted number of evaluations of the cost function. Then, one uses a genetic algorithm to locate the optimal point of the approached function in the initial configuration. From this first trial, one locates the optimal point, and one seeks the element to which the center is closest and contains it. Beside its center, one will create new elements, whose centers will be at a distance equal to half of the distance between two elements of the initial configuration. The radius of each new element will be also equal to half of the radius of the initial elements, see Figure. 1.

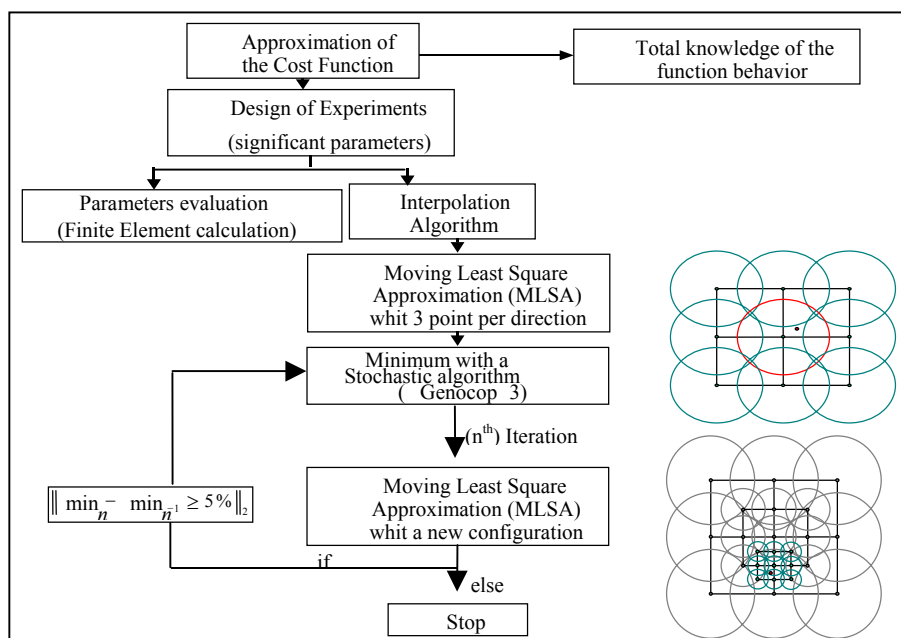


Figure 1: Adaptive parametric space discretisation through creation of new elements

2.3 Application to the Metallic Injection Moulding

In this application, one applies the adaptive method to the tensile test specimen and one compares the improvement of the optimum value with that one obtained by standard optimization strategy (genetic algorithm coupled to FEAPIM©). The optimum is obtained after 389 cost function evaluations and is given in Table 2. One

clearly observe that the values obtained from the adaptive method coupled with MLSA method are close to the ones obtained by the genetic algorithm [2] (Table 2) with an error around to 8%

Table 2: Parameters values after optimization obtained from a genetic algorithm and with the proposed optimization method

Optimization method	Evaluations number	Parameter values after optimization
MLSA + Adaptive refinement method	480	$\Phi_{S_0} = 0.505$, $\rho_f = 2.12g/cm^3$, $\rho_p = 3.55g/cm^3$, $k = 0.0015Pa.s.m^{-2}$.
Genetic algorithm coupled with the injection solver	3000	$\Phi_{S_0} = 0.5$, $\rho_f = 2.5g/cm^3$, $\rho_p = 3g/cm^3$, $k = 0.0016Pa.s.m^{-2}$.

At the second application, one applies the response surface to the implant parts (Figure 2). Taking into account computing time of simulation (24h), one optimizes two parameters: injection pressure [10-20 MPa], injection temperature [100-200 °C] by building response surface whit 3 points per direction, coupled whit a genetic algorithm. The parameters values obtained after optimization are : Pinj = 17.4 MPA and Tinj =150 °C, and the simulation result of injection phase are represented in Figure 2.

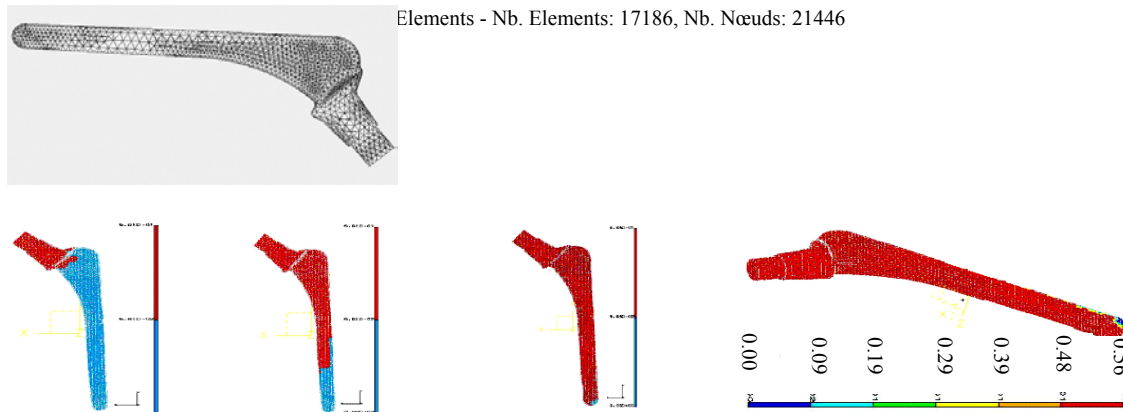


Figure 2: Mesh, filling and powder distribution of implant part using ceramic powder

3 Optimization of sintering phase

3.1 sintering model

The linear viscoplastic (creep) law is used to set up the relationship between the macroscopic strain rate tensor and the stress tensor [4], expressed as:

$$\dot{\boldsymbol{\epsilon}}^{vp} = \frac{\boldsymbol{\sigma}'}{2G} + \frac{\text{tr}(\boldsymbol{\sigma}) - 3\sigma_s}{9K} \mathbf{I} \quad (2)$$

where $\boldsymbol{\sigma}'$ is the deviatoric stress tensor, $\text{tr}(\boldsymbol{\sigma})$ is the trace of the stress tensor, \mathbf{I} is second order identity tensor, G is shear viscosity modulus, K is the bulk viscosity modulus, σ_s is the sintering stress. Different models have been developed to identify such constitutive equations. The following expressions are used in this study [5]:

$$G = \left(\frac{d_0}{d}\right)^{\frac{2}{3}} \left(\frac{d-d_0}{1-d_0}\right)^2 \frac{d r_0^3}{90D_{\text{iff}}(T)}, \quad K = \left(\frac{d_0}{d}\right)^{\frac{2}{3}} \left(\frac{d-d_0}{1-d_0}\right)^2 \frac{d r_0^3}{54D_{\text{iff}}(T)} \quad (3)$$

$$D_{diff}(T) = \frac{\Omega \delta D_{b0} e^{-\frac{Q_b}{RT}}}{kT} \quad \sigma_s = \frac{8\gamma_s}{r_0} \left(\frac{d_0}{d} \right)^{\frac{1}{3}} d$$

where r_0 is the initial radius of spherical powder particles, d_0 the initial relative density, d is relative density, γ_s is the surface energy of the particles. Diff is a diffusion term, k is the Boltzmann constant, Ω the atomic volume, δD_{b0} is a diffusion coefficient at grain interface, R the specific gas constant and Q_b is an activation energy. The main limitations of relationships in (3) are related to their validity from the initial density of the porous media to the final dense state.

3.2 Numerical identification for sintering physical parameters

The identification algorithm is designed for proper identification of material parameters in the constitutive models to be used in subsequent numerical simulations. The optimisation strategy is proposed to minimise the differences between both shrinkage curves obtained from the dilatometer experiments and numerical simulations respectively. The material parameters are the variables to be optimised. So the optimisation problem is formulated as a minimisation one expressed as:

$$\begin{cases} \min F(x) = \sum_{i=1}^n |f_e(T_i, x) - f_s(T_i, x)|^2 \\ x = [\delta D_{b0}, Q_b, \gamma_s, r_0] \end{cases} \quad (4)$$

where $f_e(T, x)$ is the shrinkage curve resulting from the dilatometer experiments, $f_s(T, x)$ is the shrinkage curve of numerical simulations and x is the set of material parameters.

The identification method is applied to get the material parameters of injection moulded alumina ceramic powders. The data given in [6] are used as reference for dilatometer experiments. The shrinkage curve obtained by using the initial material parameters which are chosen from the references is optimised in order to approach the curve obtained from dilatometer experiments as shown in Figure 3. And the material parameters of alumina ceramic powders ones after identification are listed in Table 3.

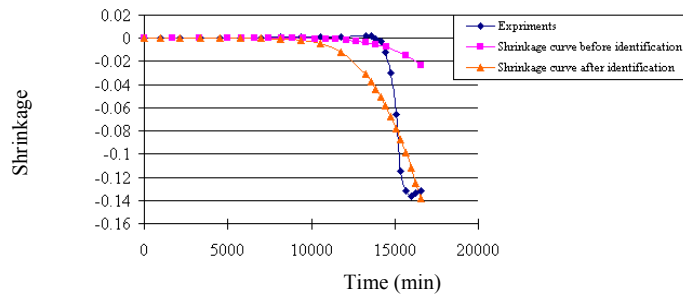


Figure 3: Comparison between experiments and after optimization shrinkage curves

Table 3: Identified material parameters

Parameters	Initial	Identified
Q_b (KJ/mol)	384	327.5
δD_{b0} (m^3/s)	8.6×10^{-10}	7.367×10^{-10}
γ_s (J/m^2)	0.71	0.8431
r_0 (m)	7×10^{-6}	5.128×10^{-6}

3.2 Application to implant part

The injection moulded hip implant parts with alumina ceramic powder are chosen as an example for the validation of the sintering model and proposed identification procedure.

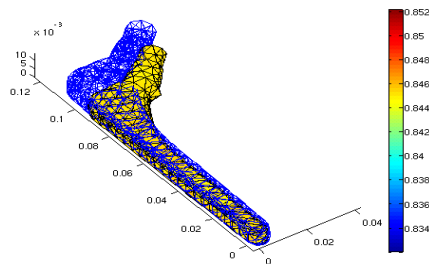


Figure 4: The initial mesh and final relative density in hip implant component

The temperature cycle for FE simulations is heating to 1400°C with the rate 5°C/min. The identified material parameters given in Table 3 are used for FE simulation. The initial mesh and the final relative density in the part calculated through simulation realised with the identified parameters is given in Figure 4. The average shrinkage is 11.85%, the final relative density is about 84.5%. That is in good agreement with the dilatometer experiments. And in experiments, the shrinkage is about 13% and the final relative density is about 95%.

4 Conclusions

An optimization methodology for optimizing process and materials in metal injection molding has been proposed, with the objective to render as low as possible powder segregation arising in the injection stage. The methodology is based on a effective combination of Design of Experiments, Response Surfaces approximation by Moving Least Square Approximation and adaptive refinement of the Response Surface Approximation. And to control the shrinkage at the end the MIM process, on has proposed to identify the material parameters, in order to correct the sintering model.

5 References

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