COST 526

"Automatic Process Optimization in Materials Technology"

(APOMAT)

Half-Yearly Report

To be sent to **V.Tesch@access.rwth-aachen.de** until **February 28, 2005**

1. Reporting Period	**01.07.2004 –31.12.2005**
Project title	Forging Process Optimization
Project leader Organization	Lionel FOURMENT CEMEF, Ecole des Mines de Paris
Main collaborators involved	Tien Tho Do, Abderamane Habbal

2. Funding Situation	
Amount of money received specifically for COST	730.6 kEuros
Other resources partially used for the project	kEuros

3. International Collaboration
(mention group and type of work done in collaboration during the reporting period)

Participation in the Working Group Meeting in Brno

☒ YES

☐ NO

Work done in collaboration:
French National funded project "OPTIMAT" gathering all the French partners of the project "APOMAT" for similar goals.

4. Industry participation
(mention name of companies and work done in collaboration during the whole project)

Setforge, Sifcor (French forging companies), Cetim (Technical Center of Mechanic Industry), CREAS, ASCOMETAL

Industrial 3D shape optimization problem: forging of a gear

5. Meetings, visits, exchange of scientists, short-term scientific missions	**Location, date**

6. Progress within the reporting period

(Not exceeding 3 pages, including tables and figures)

1 OPTIMIZATION ALGORITHMS

The BFGS algorithm is robust, efficient and well adapted to design problems. It requires computing the gradient of the objective function, and here the adjoint state method is used with semi-analytical calculations [4]. Very often, it finds a solution within few iterations, but this solution may depend on the starting point, and the algorithm may get trapped into local optima.

1.1 Evolution strategy with meta-model: ES-M

Evolution Strategies (ES) are very similar to Genetic Algorithms (GA), with slight differences. ES use real coding parameters, and the selection of the parents is simpler, with only two strategies, the “plus” (parents are kept in the new generation) and “comma” (parents do not survive) ones. Mutation is the main genetic operator, while recombination is not systematically used for producing new individuals. It is just the opposite for GA. ES may find a solution more rapidly, whereas GA are more robust to locate a global extremum. In this paper, we have used an enhanced version of ES based on a meta-model (ES-M) that has been developed at the University of Dortmund [5]. In order to reduce the number of function evaluations, a high-dimensional interpolation model, called *meta-model*, is dynamically built. It recycles the already calculated functions to better approximate the function over the optimization domain. The utilized Kriging method provides both an estimation of the function value at any point but also the confidence interval of this estimation.

1.2 Hybrid algorithm based on clustering: GA-MGC

A similar approach (GA-MGC) is utilized with a Genetic Algorithm (GA), here the one written by Pikaïa [6], and a Meta-model based on a discontinuous linear interpolation provided by the Gradient information and a Clustering method [7]. For the current population of any generation, a clustering algorithm gathers the individuals into a prescribed number of clusters. The objective function and its gradient are then calculated at the gravity center of these clusters. A linear interpolation can then be applied inside each cluster (see a 1D representation in Figure 1), allowing to compute an approximation of the function for all the individuals of the cluster. This way, whatever the population size, the function and its gradient are only evaluated for a prescribed number of points, *Nbcal.*

1.3 Hybrid algorithm based on Liszka-Orkisz extrapolation: GA-MGO

The GA-MGC algorithm does not have memory. It can possibly be improved by taking into account the *Nbeva* values evaluated during the previous generations. For any individual X_i, the objective function is continuously approximated by equation (1) (see a 1D representation in Figure 1), which minimizes the error due to the local linear interpolation in a least square sense (Liszka-Orkisz’method [8]).

$$\hat{\Phi}(X_i) = \frac{\displaystyle\sum_{j=1}^{Nbeva} \frac{\Phi(X_j) + \nabla\Phi(X_j) dX_{ij}}{\left(dX_{ij}\right)^4}}{\displaystyle\sum_{j=1}^{Nbeva} \frac{1}{\left(dX_{ij}\right)^4}} \quad (1) \qquad \Pi = \sum_{i=1}^{nbind} \left(\sum_{j=1}^{nbcal} \frac{1}{\left(dX_{ij}\right)^2} + \sum_{k=1}^{nbeva} \frac{1}{\left(dX_{ik}\right)^2} \right) \quad (2).$$

dX_{ij} is the Euclidian distance between an individual X_i of the current population and a point X_j where the function and its gradient have actually been evaluated. At each generation of new *Nbind* individuals, it is then necessary to find the best points to carry out these *Nbcal* evaluations. Assuming the regularity of the objective function, these points minimize the following functional:

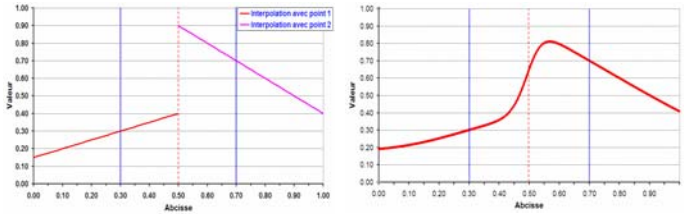

Figure 1: Linear discontinuous (based on clusters) and continuous (based on Liszka-Orkisz method) interpolations

2 APPLICATIONS

2.1 Preform optimisation of a 3D gear:

The optimization problem consists in improving the preform shape that is utilized to forge a gear (see

Figure 2), in order to minimize the forging energy (**Erreur ! Source du renvoi introuvable.**) and reduce surface defects (**Erreur ! Source du renvoi introuvable.**). $\Phi = \Phi_{ene} + \Phi_{fold}$ is used as objective function. The axisymmetrical preform is parameterized by a combination of quadratic curves (see Figure 2). 1/20 of the gear is studied. The constant volume constraint is handled by condensation, reducing the number of unknowns from 4 to 3. The computational time for a simulation with the FORGE3® software is more than 12h on a PC (Pentium4 - 2.4Ghz). For optimization iterations, a less expensive simplified problem is preferred (about 30 minutes of CPU): the mesh is coarser and the material behavior is linearized.

Figure 2: . Full preform and gear shapes *(not real scale)* - Parameterization of the geometry of the radial plane

Figure 3 shows the convergence history with the studied optimization algorithms. Figure 4 shows the best preforms proposed by each of them and Table 1 the number of simulation required and improvement of the objective function. After 3 iterations, the BFGS algorithm is not able to improve the solution utilized in industry. It is very probably trapped into a local extremum. ES-M makes it possible to find a much better solution after 42 problem simulations. GA-MGC finds a slightly better solution after 27 calculations and GA-MGO after only 7 calculations. GA-MGO finds its best solution after 17 calculations. GA-MGC and GA-MGO require computing the gradient, which multiplies the computational cost by approximately 2 in the linear case, and 1.3 in the general non-linear one.

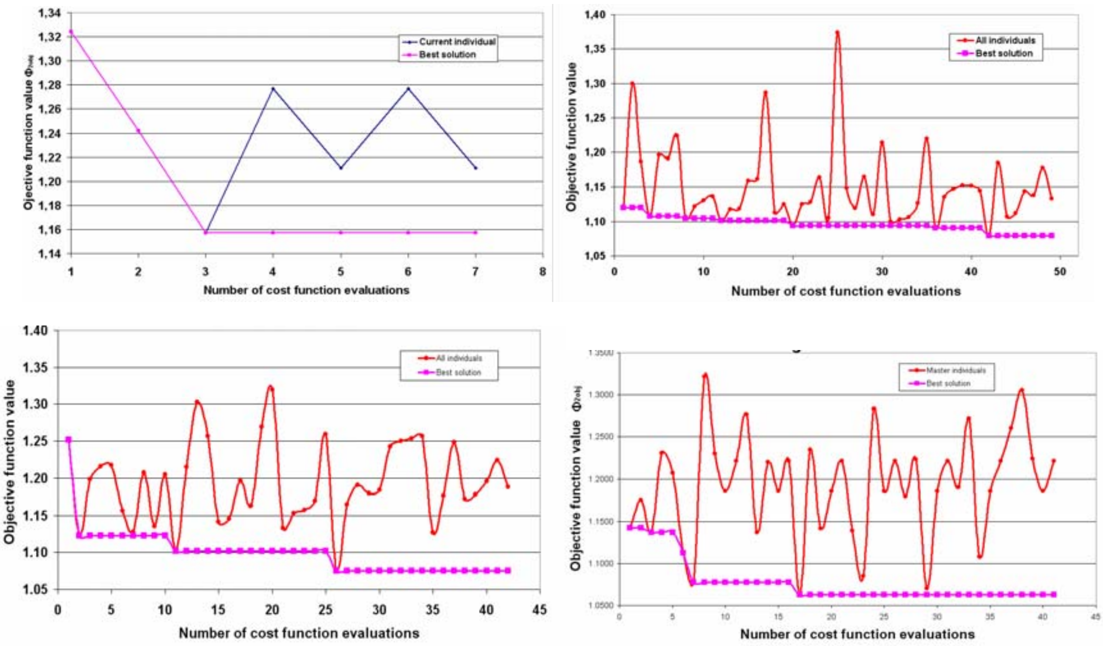

Figure 3: Convergence history respectively with BFGS, ES-M, GA-MGC and GA-MGO

This example shows the robustness and efficiency of evolutionary algorithms for complex objective functions, and the improvement brought by the hybrid algorithms.

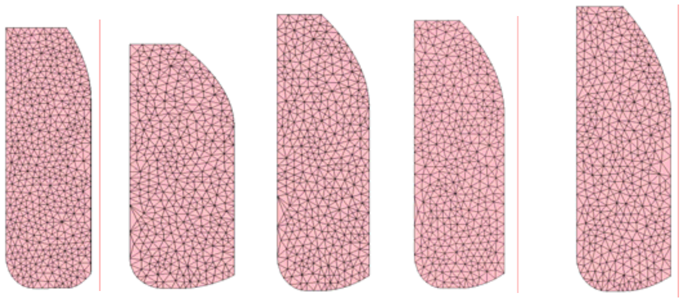

Figure 4: Preform respectively suggested by: the forging company, BFGS, ES-M, GA-MGC, GA-MGO

Table1. Optimizations results for the 3D gear forging.

	ref	BFGS	ES-M	MGC	MGO
Φ	1.19	1.15	1.08	1.075	1.06
%		3%	9%	9.3%	10.3%
Nb		7 (stag)	50	40	40

ACKNOWLEDGEMENTS

The contributions of Michael Emmerich from the Dortmund University (Germany) whithin the “APOMAT” COST 526 project, and of the Ascoforge Safe company are gratefully acknowledged.

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2 Antonio, C. A. and N. M. Dourado, Metal forming process optimisation by inverse evolutionary search, *J. Materials Processing Technology* **121**: 403-413 (2002)

3 Sousa, L. C., C. F. Castro, Inverse methods in design of industrial forging processes, *J. Materials Processing Technology* **128**: 266-273 (2002)

4 Laroussi, M., Fourment, L., The adjoint state method for sensitivity analysis of non-steady problems. application to 3D forging, *Int. J. of Forming Processes, vol. 7/1-2*, pp 35-64 (2004).

5 Emmerich, M., Giotis, A., Özdemir, M., Bäck, Th. and Giannakoglou, K., Metamodel-assisted evolution strategies, in J. J. Merelo Guervos et al. (edts.): *Parallel Problem Solving from Nature VII, Proc. Inte'l Conf, Granada*, September 2002

6 http://www.hao.ucar.edu/public/research/si/pikaia/pi–kaia.html#sec9

7 Berard, Y., J.-A. Désidéri, et al. (2003). Experiments with Hybridized Genetic Algorithms in Aerodynamics. Evolutionary Methods for Design, *Optimization and Control, Barcelona*, CIMNE.

8 Liszka, T. and J. Orkisz, The finite difference method at arbitrary irregular grids and its application in applied mechanics, *Comp. and Struct 11*: 83-95 (1980)

7. List of publications
a) Published
Lionel FOURMENT, Tien Tho DO “Gradient, non-gradient and hybrid algorithms for optimizing 2D and 3D forging sequences” The 8th ESAFORM CONFERENCE on MATERIAL FORMING(Cluj-Napoca, Romania, April 27-29, 2005
b) Submitted for publications
c) In preparation