

## Introduction of Multi-Disciplinary Optimization in Compressor Blade Design

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Reducing costs and development times are two of the main challenges for aircraft engine designers. In particular, multi-disciplinary design is a very time-consuming process. Effectively this kind of design must solve antagonistic objectives handled by different specialists and it is often a challenge to converge towards a satisfying trade-off between disciplines within the planned timespan.

Here we describe different complementary methods based on high pressure compressor (HPC) blade design. We have developed a new common geometrical model and a fully automated aerodynamic and mechanical design process which enables us to carry out multi-disciplinary optimizations with powerful algorithms.

The methodology available with these new numerical tools has been successfully applied to the design of the first stage of a HPC at Snecma. Promising results validating the gain provided by this approach are then discussed and compared to HPC blade design common experience.

### Nomenclature

<i>ANN</i>	=	Artificial Neural Network
<i>CAD-CAM</i>	=	Computer Aided Design and Manufacturing
<i>DOE</i>	=	Design Of Experiments
<i>FEA</i>	=	Finite Element Analysis
<i>GAP</i>	=	Global Assimilation Process
<i>HPC</i>	=	High Pressure Compressor
<i>LE / TE</i>	=	Leading / Trailing Edge
<i>MDO</i>	=	Multi-Disciplinary Optimization
<i>NS3D</i>	=	Navier-Stokes 3D
<i>NURBS</i>	=	Non Uniform Rational B-Splines
<i>SM</i>	=	Surge Margin
$\beta_i$	=	fluid inlet/outlet angle
$\Omega$	=	rotor angular speed
$\dot{m}$	=	mass flow
$\eta$	=	isentropic efficiency
$\Pi$	=	pressure ratio
$\sigma$	=	Von Mises stress

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## **I. Introduction**

With the improving performance of both computers and numerical methods, parametric optimization is now often introduced in the design cycle of simple isolated parts. However, optimization remains difficult to use in the case of multi-disciplinary and complex design such as HPC blade design. Effectively this design is still a complex iterative process with several goals to reach – mass flow, pressure ratio, efficiency, stall margin, operating lifetime– which requires highly expert skills in the associated disciplines: aerodynamics, mechanics and thermics.

Consequently, we cannot optimize directly all standard design parameters of each discipline because they would be too numerous in the context of industrial design cycle. Moreover, we must transform the current process, independant aerodynamic and mechanical optimizations, into a parallel and integrated process by introducing a cost function relevant with a multi-disciplinary approach. Finally we have to solve complex coupled non-linear optimization problems.

Snecma is involved in two complementary projects to overcome these difficulties.

The first one deals with the improvement of the iterative design process. We have succeeded in providing a new common definition for blade geometries based on a continuous surface, better than the previous definition based on sections, and a new designer-friendly blade modeler which simultaneously takes into account aerodynamic, mechanical and manufacturing constraints. The development of this parameterized model is the first step for the introduction of a new multi-disciplinary HPC blade design process.

The second project should help us to reach two ambitious goals : to provide fast and robust optimization algorithms using up-to-date mathematics, then to demonstrate design cycle time reduction and innovative concept development using these algorithms on industrial cases. Among the identified cases, the improvement of HPC blade design was one of the most challenging due to the antagonisms between aerodynamic and mechanical criteria.

In this paper we will first describe the new blade modeling strategy and its introduction in the newly adapted HPC blade design process, then we will focus on a particularly efficient optimization algorithm developed by the Mathematical Institute of Toulouse (IMT) based on an artificial neural network (ANN). In the third part we will show how these new tools can help designers improve directly aerodynamic and mechanical performances with the presentation of a HPC blade aerodynamic optimization under mechanical constraints.

## **II. A new blade model**

### **A. Introduction of a common blade definition**

The previous standard blade geometry definition was “discrete”: the blade was described by several sections, either plane or linked to a flow path, in the form of lists of points. This definition comes from the first step of aerodynamic compressor blade design. Effectively to match pressure or Mach number distribution along streamlines imposed by the first 2D performance computation, we use a 2D inverse method which gives sections.

Although this description with points is simple to use, it has several disadvantages for the next step of the blade design. The main problem is its non-continuous definition : between sections, the blade geometry is dependent of the interpolation algorithm used in CAD-CAM tools. Another default is the lack of bijection between a blade defined by plane sections, used by mechanical designers, and a blade defined by aerodynamic sections, introducing discrepancies in the long iterative design process.

Consequently, we decided to replace the section-based definition of the blade by a unique mathematically rigorous surface. The same object is handled via this new standard definition throughout the various phases of the process. The selected format, NURBS, allows to describe complex geometries and is implemented in most CAD tools and in particular CATIAV5, the CAD-CAM software selected by Snecma.

A Snecma in-house tool, TurboGeom, creates the NURBS surfaces from initial sections, using the global interpolation method described in Ref. 1 and, optionally, a smoothing algorithm to avoid potential oscillations. This results in a unique blade definition described by two high quality surfaces, the suction side and the pressure side, with tangential continuity along the LE and TE (cf. Fig 1).

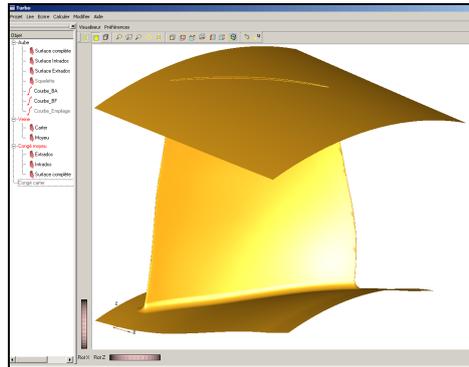


Figure 1. Blade NURBS Surface in TurboGeom

Now mechanical and aerodynamics designers use the same blade definition in their own design iteration.

**B. SuMo : the Surfacic Modeler**

As all designers will work on the same surfacic blade definition, we must give them possibility to modify it. Moreover, for the modeler to be used in optimization processes, it must integrate a clever parameterization that respects geometric constraints to obtain a continuous design domain and limits the number of variables to control the blade surfaces.

These are the two main ideas which drove the development of SuMo. Consequently, SuMo is a modeler based on well-known design parameters rather than a purely geometrical modeler. It allows to modify an initial blade surface created with TurboGeom through 2/3D delta laws defined by designer. Figure 2 explains how SuMo works with low compressor blade example.

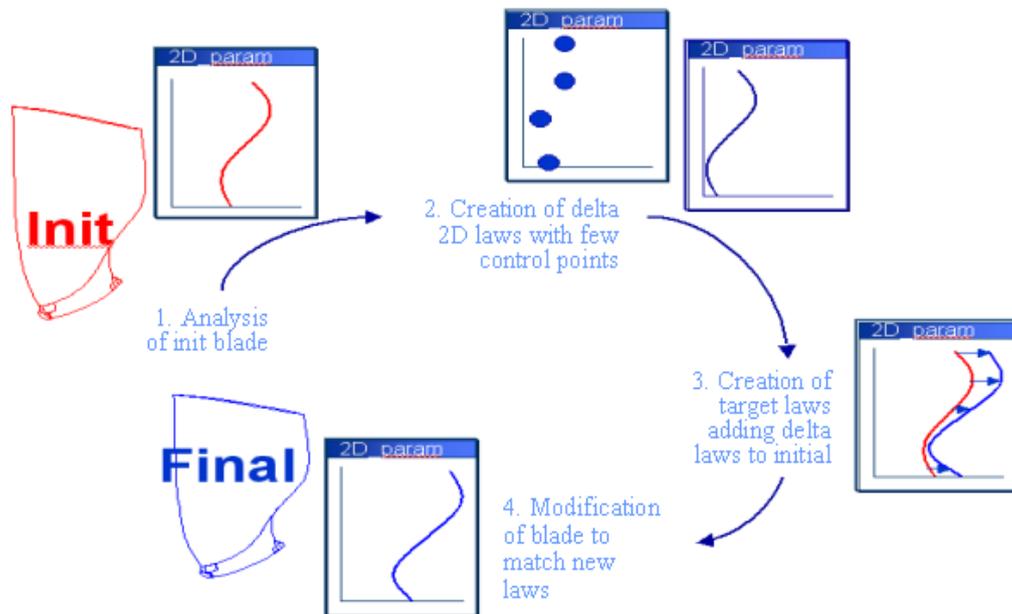


Figure 2. SuMo description

The available parameters include 2D parameters like the inlet and outlet solid angles, the stagger angle, the center of gravity, the chord, the maximum thickness and its position.

### C. Improvement of compressor blade design process

The design of a compressor blade is currently performed through so-called “aero-mechanical iterations”. In practice, the goals of mechanical design - low stresses to increase operating lifetime - and aerodynamic design - pressure ratio and mass flow - often lead to opposite designs. For example aerodynamically, thickening the blade introduces flow losses while it improves mechanical behavior as long as mass does not increase too much.

The old design process was iterative and manual (cf. Fig. 3a). It implied numerous iterations and at the end engineers had to reach a compromise between performances in the different disciplines. Furthermore, the lack of a single model hindered exchanges of blade geometries between engineers during the iterations.

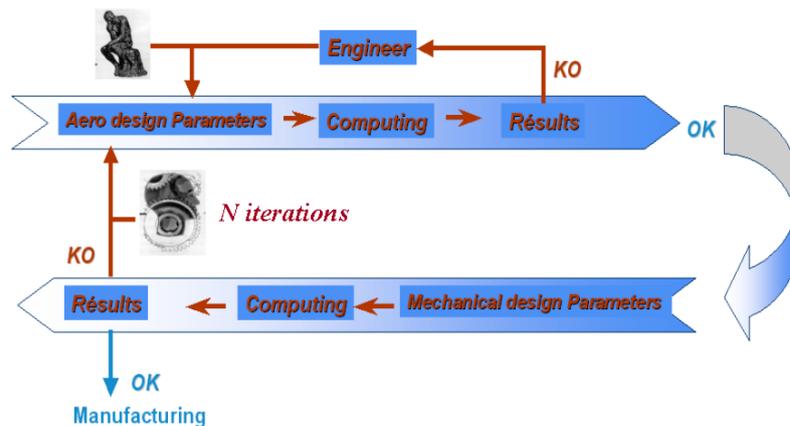


Figure 3a. Description of the old iterative process

With the new tools described above we can propose a simplified parallel process which makes exchanges easier between the different design disciplines and introduces multi-disciplinary optimization (cf. Fig. 3b). The first step of this new process is performed with TurboGeom in order to create the initial blade surface, then designers use SuMo to modify blade surfaces during the optimization loop.

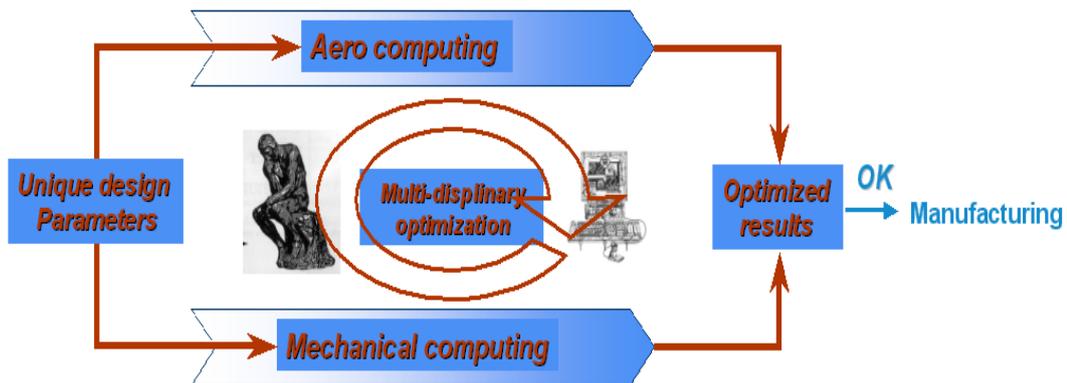
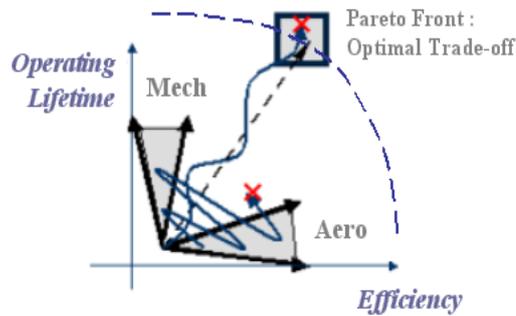


Figure 3b. Description of the new parallel process

Another improvement is to do with the treatment of blades geometry depending on the rotational speed of the module which they take part. A compressor blade with a thickness to chord ratio inferior to 15 % is subject to major deformations between its “cold” or manufacturing geometry and its “hot” or cruise geometry which corresponds to a high rotor speed . The link between “cold” and “hot” geometries is complex and was one of the causes of divergence

between mechanical and aerodynamic designs. Thanks to recent progress in the Samcef solver<sup>2</sup>, Snecma has succeeded in computing the “cold” geometry from the initial “hot” one in only one inverse non-linear computation.

The second advantage of this new process is due to the natural introduction of a multi-disciplinary compromise during design which speeds up and improves the final result because iterations converge faster towards an equilibrium between opposite goals (cf. Fig. 4).



**Figure 4. Advantage of multidisciplinary  
integrated process**

### III. Efficient optimization algorithm

#### A. Artificial Neural Network for optimization

Many optimization strategies proved their efficiency in aerodynamic or mechanical blade design<sup>3, 4</sup>. We can divide these strategies into two groups. The first strategy tries to optimize the problem directly by computing the cost functions on the whole numerical model for each iteration, whereas the second strategy uses a surrogate model.

In industrial multi-disciplinary blade design, a direct optimization using 3D detailed model would take too long in computing time and it could only be efficient using a linearized model provided by adjoint techniques. This method is not yet validated for low-Reynolds flows even if many studies underline interesting progress<sup>5</sup>.

Surrogate model approach has at least two major advantages. It allows the use of powerful optimization algorithms as computing time does not increase highly with the number of objectives evaluation because they are computed analytically using the surrogate model. What is more with this strategy, designers can still learn about correlations between parameters and objectives post-processing the surrogate model even if the final result of the optimization does not satisfy them.

Building a surrogate model is an open problem with many algorithms available: response surfaces, artificial neural networks (ANN), polynomial regression, kriging, multivariate adaptative regression splines, radial basis functions<sup>6</sup>. Interesting properties of these models should be their ability to efficiently detect sensitive parameters and to catch global non-linear behavior starting from a linear number of initial sample points with regards to the number of parameters.

In the last decade, ANN have become one of the most popular solutions because of their properties regarding these two major characteristics.

#### B. GAP : Global Assimilation Process

The IMT laboratory has developed a three-layer ANN (cf. Fig. 5), chosen for its quality of universal approximator in the case of continuous functions. The GAP software was initially programmed during previous thesis<sup>7</sup>. It is characterized by a supervised training of the ANN based on a low memory Levenberg-Marquardt algorithm using the forward and reverse modes of the algorithmic differentiation. It also combines several regularization techniques to assume generalization qualities.

This last point is particularly important because it enables a better training of the ANN avoiding over-learning and local minima attraction which are common problems with these kinds of algorithm.

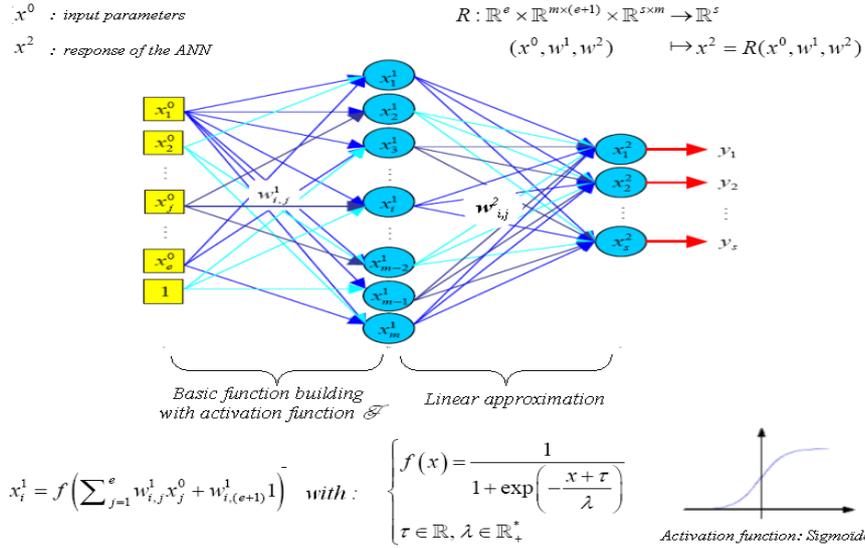
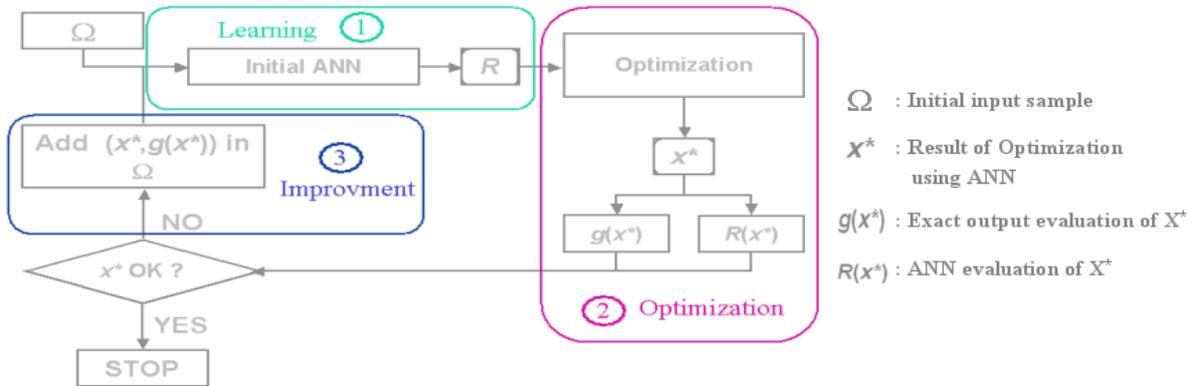


Figure 5. Description of a three-layer neural networks

Using this metamodel, an iterative process with successive optimizations on an ever improved neural network is carried out. This idea has been validated as a pertinent way to optimize aerodynamically a blade design for the last five years<sup>8,9</sup>.

The basic diagram of this process is shown on the following scheme :



We use GAP in a modular way to keep the possibility to modify how we will use the three phases of the process: learning, optimization and improvement. Effectively, we can change the algorithm of optimization phase or the strategy of ANN improvement.

For example a first possibility adds regularization during the successive neural network training mixed with gradient-based algorithm for the optimization phase. In this manner we obtain finally an approximated model catching accurately the cost function close to the optimum and only the global tendencies of the function in the other parts of the design domain. The idea behind this strategy is to learn only what interests us which minimizes the number of real function computation. The figure 6 shows the result of such an approach. We can remark that the final model fits the trend of the parabolic Rastrigin function without following the finest variations introduced by the cosine which may simulate function local minima or even numerical noise due to remeshing.

In a second way, we will try to learn as much as possible about the problem everywhere in the design domain then we optimize on this precise approximated model with a genetic algorithm to catch the global minima. This method generally needs more points than the previous approach, but we can monitor in real-time its generalization abilities with a measurement process such as cross-fold validation<sup>10</sup> to verify that we have not overfit the data. This is the main risk with this approach whereas the previous strategy can sometimes miss interesting local behavior.

The possibility to easily combine several validated elementary algorithms is a major gain for Snecma because we no longer need to store and support a large number of black-box algorithms each with their own specificities. On contrary we have built an efficient optimization toolbox usable for all optimization problems.

### C. Improvement of GAP for blade design

From the initial GAP software, recent work<sup>11</sup> handles the improvement of the optimization step in GAP in the context of the first methodology described above, regularization and gradient optimization.

This recent work adds three algorithms to speed up the convergence of the optimization:

- § domain control adaptation,
- § point stacking escape,
- § introduction of a maximum of the cost function during optimization

#### 1. Domain control adaptation

The optimization method developed in GAP for the gradient optimization approach starts with a small DOE whose size is proportional to the number of parameters. Thus we limit the risk of being quickly caught in a local optimum, but unfortunately this slows down the second iterative phase of the optimization.

To remedy this problem, we introduce an adaptive strategy to narrow the design space. If two successive optima do not vary with regards to a particular parameter, we will reduce the initial range of this parameter and similarly an abrupt variation related to one parameter will increase the research domain size for this parameter, obviously without extending the initial domain limit.

The idea, inspired by trust region methods<sup>12</sup>, is therefore to progressively reduce the range of those parameters that have no influence on the optimization process.

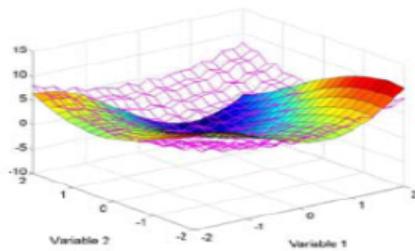
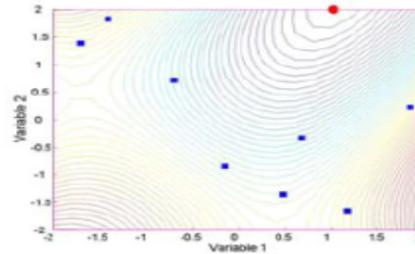


Figure 6a. Initial ANN



8 points in initial DOE

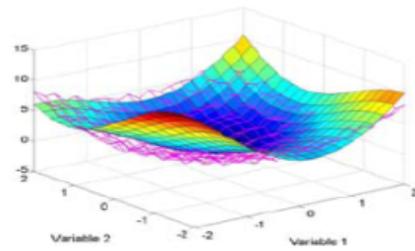
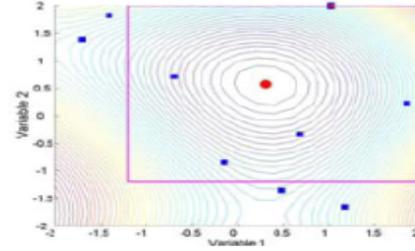


Figure 6b. Iteration 1



1<sup>st</sup> Optimum computed and added to initial ANN

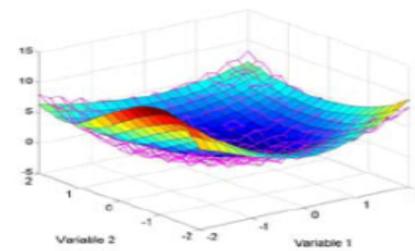
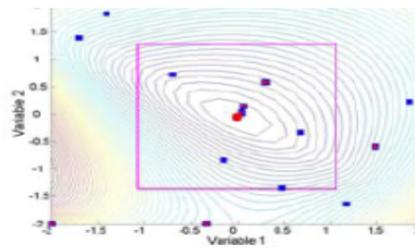


Figure 6c. Final iteration



Final Optimum found with the ANN in the reduced domain control

Figure 6. Example of optimization with GAP on Rastrigin function using domain control adaptation

### 2. Point stacking escape

As we near convergence during the gradient optimization phase, the last points accumulate and this limits precision of the ANN which loses its generalization abilities. Consequently a geometry-based method substitute a new point for the optimum result of the running iteration. This new point respects two constraints: to be in a sphere centered on the computed optimum with a radius which is a parameter of the algorithm and to be as much as possible at equal distance of the optimum of the previous iteration.

This method prevents the final loss of generalization when we are close to convergence and reduces significantly the distance between the optimum of the objectives and the final point given by the algorithm.

### 3. Introduction of maximum solution during optimisation

The Tabu search, introduced by F. Glover in the late 80's, is an heuristic local search method used to solve complex problems. The aim of this method is to accept to sometimes follow an unexplored and unpromising direction to escape from local minima.

In the Gap optimization phase, we translate this idea by adding a point with a high value on top of the optimum for the successive training of the neural network. This maximum is computed only in domains where the ANN has few information.

Consequently, we improve the knowledge of the global tendencies of the problem which will speed up the convergence of the optimization process.

## D. Results : Optimization improved with new algorithms

We have carried out many tests on analytical functions in order to validate the different methods presented in §3.2. Here we will detail our results. We compare the error on the exact optimum of the function for each algorithm for a fixed number of function evaluation.

Test functions used are:

Carredec Function:  $F(X) = \sum_{i=1}^d (x_i - 2 + 4 \frac{i-1}{n-1})^2$ ,  $X \in [-3; 3]^d$ , with d=dimension

Neumaier Function:  $F(X) = \sum_{i=1}^d (x_i - 1)^2 - \sum_{i=2}^d x_i x_{i-1}$ ,  $X \in [-d^2; d^2]^d$ , with d=dimension

Trig Function:  $F(X) = d - \sum_{i=1}^d \sin(x_i)$ ,  $X \in [-\pi; \pi]^d$ , with d=dimension

In Table 1, M1, M2, M3 and M4 represent:

M1 is initial optimization method with regularization and gradient optimization,

M2 = M1 + improvement strategy: domain control adaptation,

M3 = M2 + improvement strategy: point stacking escape,

M4 = M3 + improvement strategy: introduction of maximum solution during optimization

Dim.	Functions	Error on optimum (*) for <b>fixed number evaluation</b>			
		M1	M2	M3	M4
6	Carredec	5e-3		1e-3 (80%)	1e-4 (98%)
	Neumaier	1e-3		5e-2 (50%)	5e-2 (50%)
	Trigo	5e-1	5e-2 (90%)	5e-3 (99%)	5e-3 (99%)
10	Carredec	1e-2			5e-3 (50%)
	Trigo	5e-1	5e-2 (90%)	1e-2 (98%)	5e-3 (99%)

**Table 1 : Analytical results for different strategies**

(\*) Gain (X %) is calculated with formula:  $(M1 - M_{(2,3,4)}) / M1$

We observe in Table 1 that these strategies provide a significant improvement of the accuracy of the function's optimum for a fixed number of evaluations. In the same way, if we reverse the problem and work with a convergence criterium, the method M4 will need fewer function evaluations than method M3 to reach the optimum.

## 4. HPC Blade Optimization

### A. Building optimization process

The strategy for parametric optimization at Snecma is generic. We divide it into four steps :

- § Identification of standard design process to automate
- § Creation of the identified workflow and dataflow in the Optimus platform
- § Choice of objectives, constraints and parameters
- § Selection of the best adapted optimization algorithm to explore the design space and carry out optimization and/or robust design.

Thus we do not attempt to develop specific numeric analysis tools which would not be used for the standard design. However this decision drives our development program roadmap because we require for every numerical tools taking part of an optimization process to ever ensure this specification.

Most of our design and analysis tools are therefore plugged into the optimization platform selected by Snecma, Optimus. This software, developed by Noesis (cf. Fig. 7), already includes drivers to connect with commercial FEA solver like Samcef or Abaqus and CAD platform like CatiaV5. Then Optimus provides all state-of-the art local, global, robust and multi-objective algorithms<sup>13</sup> as well as the possibility to easy integrate our own algorithms such as GAP.

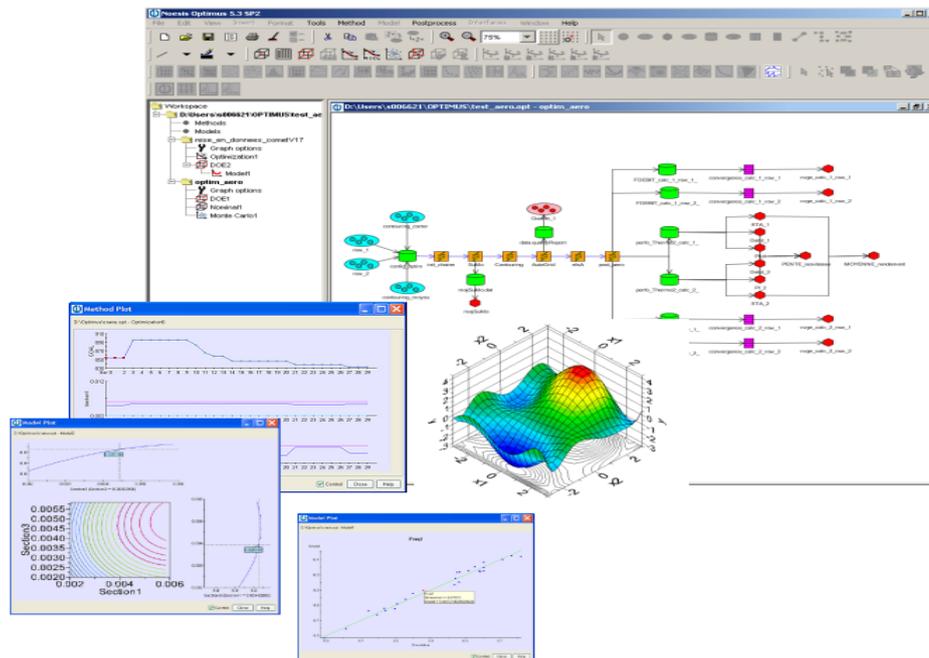


Figure 7. Example of template and post-processing generated with Optimus

### B. Description of multi-disciplinary optimization

#### 1. Introduction to Snecma HPC blade design

HPC design is a challenging issue because of its role in operability and specific fuel consumption and consequently the difficulties to provide high performance and stability assessment with efficient matching of the whole compressor stage without decreasing vibration and stress margins on components with high speeds. The documentation on this subject is very rich and we suggest that interested readers refer to Ref. 14 and 15.

As we translate the new parallel process discussed in §2.3 with tools adapted to Snecma HPC design (cf. Fig. 8), we introduce the following program in order of appearance in the process : SuMo for blade modeler, Patran and Autogrid for mechanical and respectively aerodynamic pre-processing (mesh, boundary conditions), Samcef for FEA and elsA for NS3D solver, then several minor Snecma tools for post-processing and process integration.

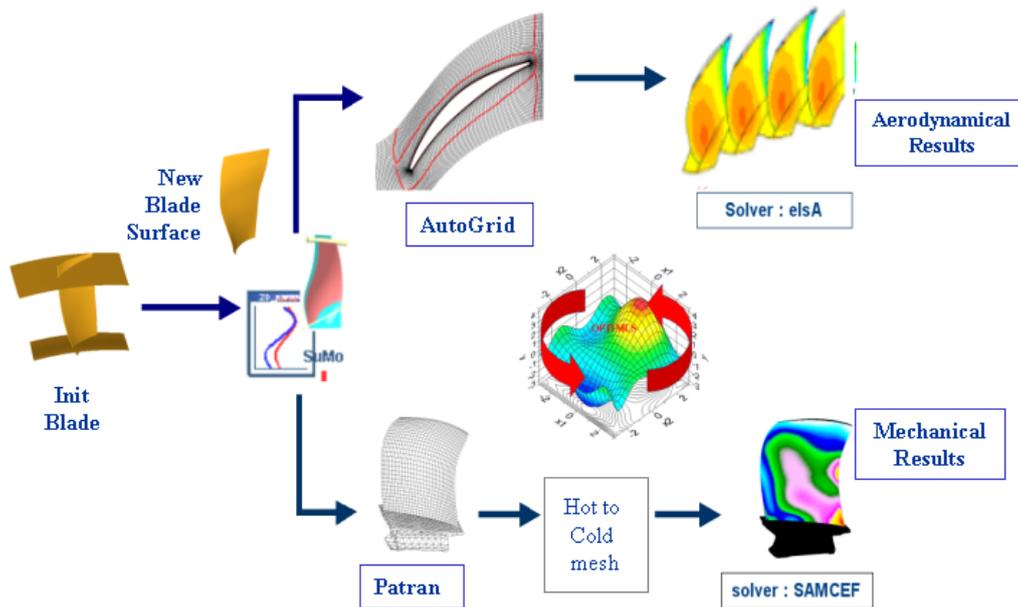


Figure 8. Tools and process for HPC blade optimization

For aerodynamic computation we use a periodic mesh with the standard O-4H topology with two million cells for the stage composed of a rotor and a stator (cf. Fig. 9). Effectively we do not use coarse grid to avoid optimizing unvalidated configurations providing wrong improvements that we would notice too late during the last validation phase. We also initialise the computation with the pressure field of the initial blade in order to reduce the number of iterations required to converge the NS3D computation for each experiment.

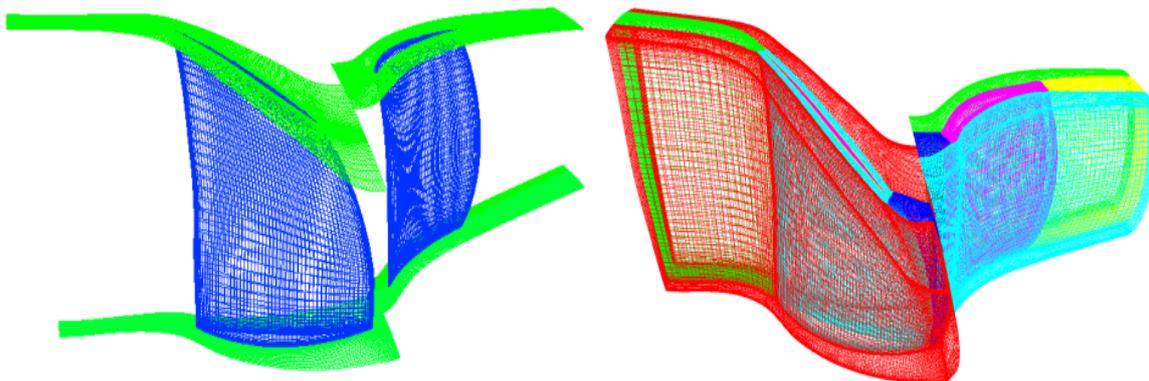


Figure 9. View of aerodynamic mesh for a full compressor stage

For the mechanical computation we have the possibility to use a reduced model by introducing a super-element for the disk part (cf. Fig. 10) which is divided into periodical sectors using cyclically symmetric approach. This allows to take into account advanced dynamical criteria such as crossings between blade eigenfrequencies and rotor harmonics for a wide frequency range.

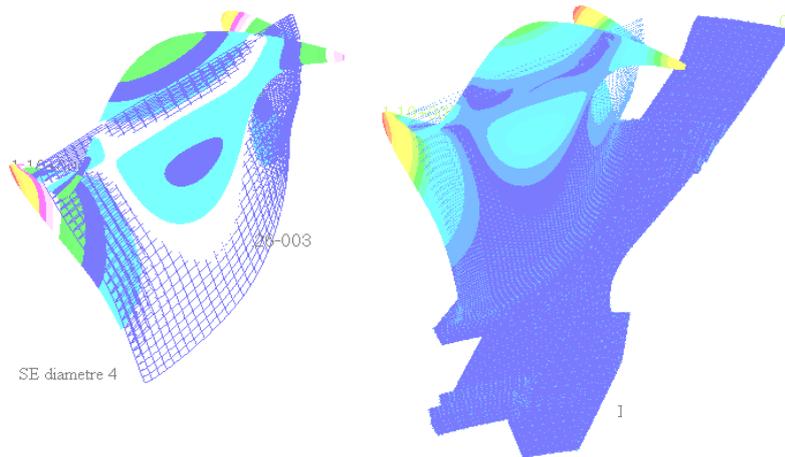


Figure 10. Validation of disk SE (left) with example of high frequency stripe blade mode

Using a supercomputer, a single experiment comprising two NS3D computations and six dynamic and static mechanical computations for 2 diameters takes three hours. We have possibility to transform our sequential optimization scheme into a parallel one especially during the initial DOE phase which reduces the final computation time.

## 2. Definition of the MDO problem

We have carried out many optimization attempts in order to validate the selection of sensitive parameters and of the best cost function to improve HPC blade design. In the next paragraph we present the results of an aerodynamic optimization under mechanical constraints for an HPC stage.

We start from a rotor blade with good efficiency and mass flow characteristics while respecting most of the static or dynamic margins. The aim of the described optimization is to improve efficiency at the design point, close to the operating line and for cruising speed, but in a multipoint strategy. Effectively it is very important to be convinced that all the forget constraints would be taken by the optimizer like some degree of freedom for its research. Consequently we will face to unexpected changing at the end of the optimization process for the function we would not have add to constraints.

Let's precise the optimization problem :

$$\begin{array}{l}
 \max_{DS} \eta_{DP} \\
 \left\{ \begin{array}{l} r_{k_{DP}} \geq \text{init} \\ \eta_{SM} \geq \text{init} \\ \Pi_{SM} \geq \text{init} \end{array} \right. + \left\{ \begin{array}{l} \Delta_{\text{shroud\_contact}} \leq SDR \\ \Delta_{\text{BA\_BF}} \leq SDR \\ \sigma_{\text{max}} \leq SDR * R_{0,2-3S} \\ \Delta_{3N\_freq1} \geq SDR \\ \Delta_{6N\_freq2} \geq SDR \\ \Delta_{6N\_freq3} \geq SDR \end{array} \right.
 \end{array}$$

with DS = Design Space, DP = Design Point, SM = Surge Margin and SDR = Snecma Design Requirement  
 $\Delta$  = blade displacement and  $\Delta i N\_freq j$  = margin between  $i^{\text{th}}$  rotor harmonic and  $j^{\text{th}}$  blade eigenfrequency

The constraints are drawn on the following characteristic graph of the stage (cf. Fig 11a) and rotor blade campbell diagram (cf Fig 11b).

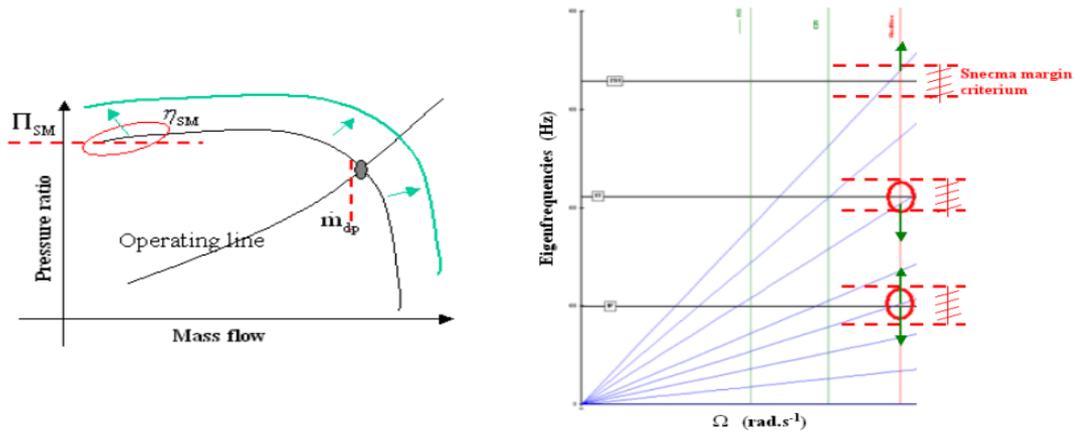


Figure 11a. aerodynamic constraints

b. dynamic constraints

Aerodynamic constraints must force the initial characteristic to be at least preserved for all off-design point.

Although it is mainly an aerodynamic gain we are seeking, we will not change specific aerodynamic parameters such as  $\beta_1$ ,  $\beta_2$  for the two following reasons : initial blade was already optimized with regards to these parameters and they do not have any influence on mechanical criteria whereas we also have to improve dynamic margins.

The optimization process will consequently modify four parameters on the rotor blade : position of sections' center of gravity, also called blade sections' stacking, to give lean and/or sweep effect on blade, then chord and thickness. The stator is not modified. Every parameter is controled with four variables along the height of the blade. At the end we move 16 parameters to optimize the rotor 3D geometry.

### C. Results

We have summarized values of the criteria for the initial blade in table 2. Aerodynamic criteria are normalized value and mechanical are given with their distance in percent to the Snecma Design Requirement. If the value is negative, we do not respect the criterium.

	Aerodynamical criteria				Mechanical criteria					
	$\eta_{dp}$	$m_{dp}$	$\eta_{SM}$	$\Pi_{SM}$	$\Delta_{shroud\_contact}$	$\Delta_{BA\_BF}$	$\sigma_{max}$	$\Delta_{3N\_f1}$	$\Delta_{6N\_f2}$	$\Delta_{6N\_f3}$
Init	1	1	1	1	+0.5	-4	+54	+7	-5	+2.5
Status	✘	OK	OK	OK	OK	KO	OK	OK	KO	OK

Table 2. Criteria value of initial blade

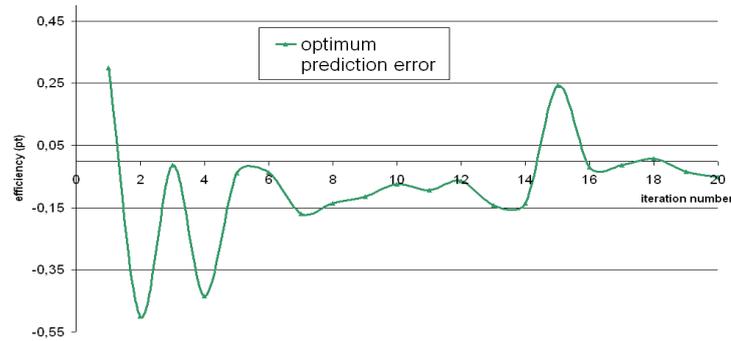
We test the two strategies described in §3.2 on this problem with parameters indicated in the table 3.

	Regularization	Input layer	Output layer	Hidden layer	Initial learning data	Pair for Generalization	Number of added experiments
GAP_1	YES	16	10	7	32	2	25
GAP_2	NO	16	10	7	40	0	25

Table 3. Gap parameters

#### 1. Gradient on regularized ANN (GAP\_1)

This approach gives good results for isolated mechanical problems like bend momentum balancing but in this case we do not succeed in improving efficiency respecting all the constraints whereas we obtain good quality of generalization for the objective as graph on optimum prediction error shows (cf Fig. 12). In fact the main difficulty for GAP with this problem has been to regularize mechanical constraints because these are the output with the maximal prediction error. Consequently the iterative gradient optimization phase on the ANN drives us in direction of unacceptable design area where frequencies and maximal static stress constraints became all violated.



**Figure 12. Error of the ANN predicted optimum for efficiency at design point**

### 2. Evolutionary algorithm on ANN (GAP\_2)

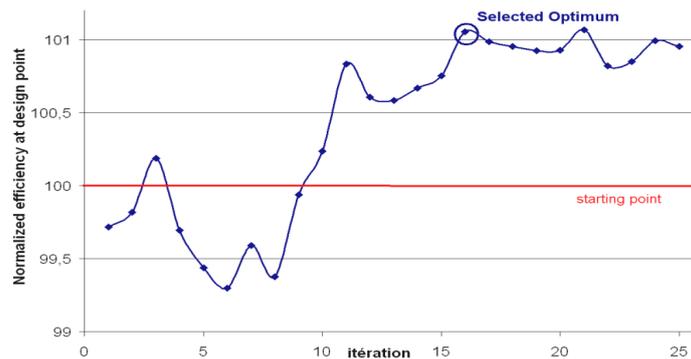
With the second strategy, the differential evolution algorithm (DEVO) available in Optimus is launched on the ANN with a population size of 160 and high crossover probability (0.85) because previous local and GAP optimization showed us the non-linearity of the problem. We fix the maximum number of population for the DEVO at 100.

Within this approach, ANN catches both the non-linearity behavior of the second bending and of the first torsion modes. We obtain at the 16<sup>th</sup> iteration a promising new geometry which respects all the mechanical criteria even the two which were KO for initial blade (cf. Table 4).

	Aerodynamical criteria				Mechanical criteria					
	$\eta_{dp}$	$\dot{m}_{dp}$	$\eta_{SM}$	$\Pi_{SM}$	$\Delta_{skroud\_contact}$	$\Delta_{BA\_BF}$	$\sigma_{max}$	$\Delta_{3N\_f1}$	$\Delta_{6N\_f2}$	$\Delta_{6N\_f3}$
Init	1	1	1	1	+0.5	-4	+54	+7	-5	+2.5
Optimum	1.012	1.065	0.997	0.992	+0.3	+25	+33	+9	+1	+2.1

**Table 4. Results of optimum new blade**

As often the objective is worse than the initial in the first iterations because ANN has not learned yet everywhere with precision whereas with global algorithm we explore all the design space. However, after ten iterations, it matches enough the design point efficiency to ever find an optimum with great improvement with regards to initial geometry (cf Fig. 13).



**Figure 13. Convergence graph**

We gain at the selected iteration more than 1% on design point efficiency which is a very interesting result close to the final result of a classical design cycle. Moreover we obtain it with only one optimization which takes 5 days and involved 140 full NS3D computations of two rows.

The final geometry was slightly different from the initial one (cf. Fig. 14 a) and all the parameters have moved during the optimization process as we can see with the 4 chord laws drawing at different iterations (cf. Fig. 14 b).

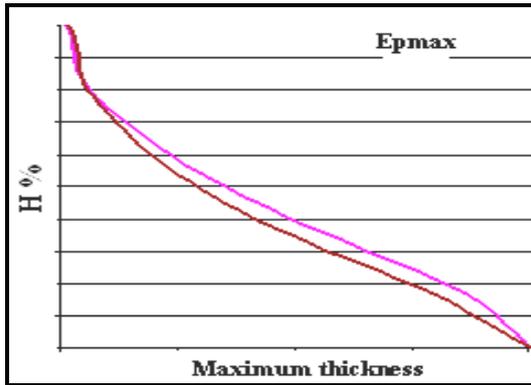
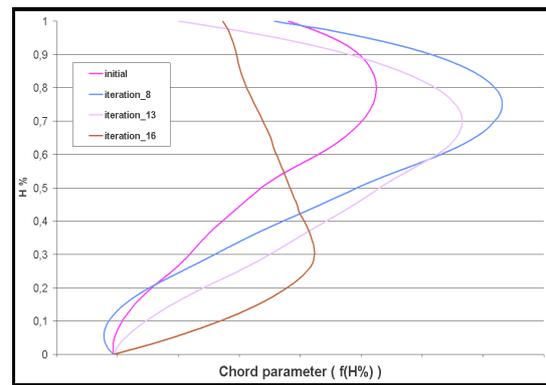


Figure 14 a. Optimum law for parameter  $E_{pmax}$



b. Chord law variation

Chord parameter influences all the criteria but especially frequencies margins and maximal static stress value. We can notice it was a very active constraint for this optimization to respect both the frequency margin between the 6<sup>th</sup> rotor harmonic and the 2<sup>nd</sup> rotor blade eigenfrequency, • 6N\_F2, and the • 6N\_F3. Their antagonistic behavior is clearly shown on figure 15a where we can count only 8 experiments out of 25 which respect the two required margins. Effectively, it was difficult to get a more softness blade for the 2<sup>nd</sup> eigenfrequency blade, first torsion mode, while keeping the second bending mode stiff enough. However the optimum selected ensures the respect of the margin around the 6<sup>th</sup> harmonic for rotor speed superior to cruise speed. We still keep a 6N\_F2 crossing for an idle speed which is not fully satisfying but anyway we have improved the initial status (cf. Fig. 15 b).

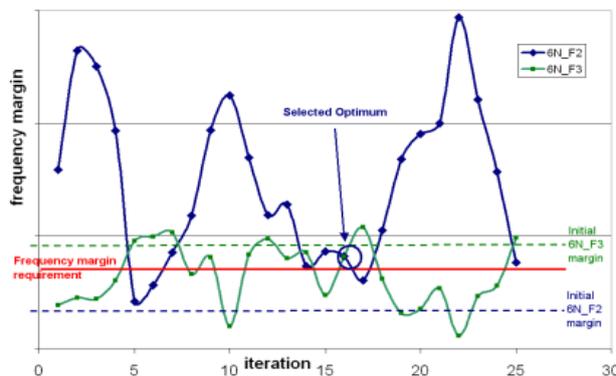
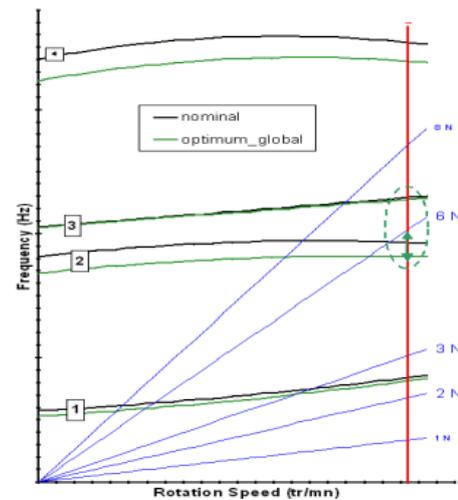


Figure 15a. 6N\_F2 & F3 margin during optimization



b. Campbell diagram of optimum blade

Another major difficulty deals with the value of maximal static stress on the blade. Effectively the new optimum rotor blade have pronounced forward sweep and local positive lean at casing which are well-known as acting positively on efficiency and surge margin. But at the contrary, it is also an origin of static overstress because it increases, under the effect of centrifugal forces, the tensile stress of the suction side which is obviously very negative for the operating lifetime. The new chord and thickness laws provided by the optimization balance the effect of the new stacking laws enough to finally respect this static mechanical criterium (cf. Fig. 16).

Now if we focus on the aerodynamic gain, we observe two major improvements on the performances of this stage.

Firstly we have increased polytropic efficiency more than one percent at the design point very close to the maximal efficiency point (cf. Fig 17a). If we detail this gain, we notice on the radial efficiency distribution (cf. Fig. 17b) that the improvements are located in the middle of the blade.

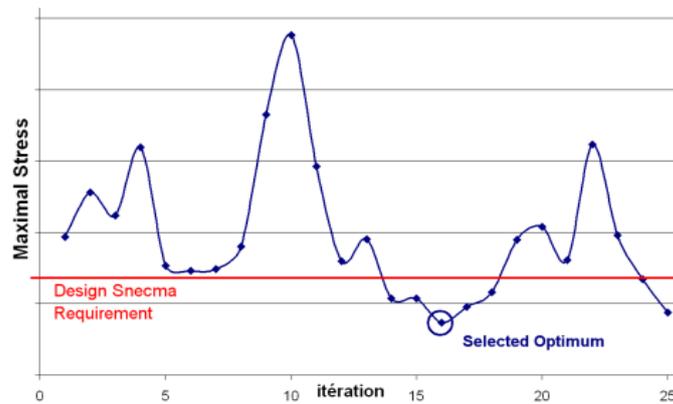


Figure 16. Maximal blade stress during optimization

Drawing the isentropic mach number along the chord for a section with a radius of 40% of the total blade span (cf. Fig. 17c), shows us a better smoothing of the Mach distribution as well as a reduction of the Mach number in front of the passage shock which explains why the losses have dropped.

Secondly, the compressor stability seems to be better. Effectively, we have also increased the numerical stall margin (cf. Fig. 17a) which is a major point for compressor operability. Indeed the compressor have better abilities to accept low mass flow condition.

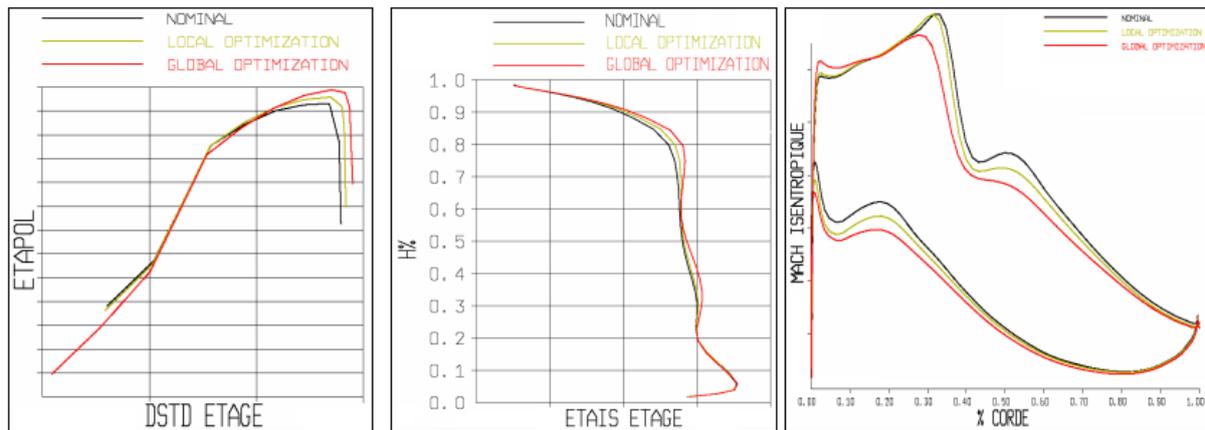


Figure 17a. Mass flow against polytropic efficiency

b. Radial isentropic efficiency distribution

c. Isentropic mach number – 40%

In the figure above, we also indicate the results of a direct gradient-based aerodynamic optimization, local optimization in the legend. With this optimization, we have achieved less than half of the efficiency gain of global optimization. No improvement was introduced close to surge point and moreover we had not taken in account the mechanical criteria in this optimization which were absolutely not respected as we finally verified. It emphasizes the great progress provided by the introduction of this multi-disciplinary optimization process associated to ANN.

## 5. Conclusions

In this article we demonstrate how the improvements of the blade geometrical definition and of the process design are necessary in order to implement powerful multi-disciplinary optimization schemes. A highly efficient optimization algorithm developed in collaboration with the IMT Laboratory provides interesting results to reduce design cycle time and to obtain a better design respecting all constraints.

Especially on the example selected, we notice how the optimization algorithm can greatly help engineers to find the optimal compromise between many objectives and constraints. Even if we already know the physical effect of the proposed optimum geometry in the separated disciplines, it is very difficult for engineers to qualify exactly the influence of each parameter in order to reach a geometry as interesting as the optimum found with the multi-disciplinary scheme. It must also be underlined how important the physical review of the optimization results is, to discuss their validity and to allow experience feedback for design.

Many complementary methods will be studied to continue this multi-disciplinary optimization project.

Firstly, we must work on the algorithm. In particular, we will focus on the possibilities of making a better selection of the initial DOE data. The second aim of the thesis<sup>11</sup> was to test the “sparse grid” numerical technique<sup>16</sup> which leads to an adaptive selection of initial data points in order to improve the initial knowledge of the problem with a minimal number of expensive evaluations. This is promising work currently in progress.

We will also naturally introduce in this multi-disciplinary problem a multi-objective approach such as well-known Pareto front concept to estimate more accurately the trade-offs between several objectives. It would be especially dedicated to aeromechanical optimization of fan blades, which implies a multi-speed optimization to avoid flutter.

Another global direction of progress will be the reduction of computing time for each problem evaluation from a physical point of view, in addition to that provided by mathematical techniques such as metamodeling. This is called the multi-fidelity approach and consists in using lower-fidelity models. If they are well managed, they can perform the major part of the optimization with a lower computation cost. We also will test another way to reduce this computing time. Optimization for detailed level design needs ever more powerful and efficient computation means. Supercomputers will continue to increase their memory capacities and numerical tools will be more and more massively parallel but we can directly act on the optimization process to reduce computation time. For example an optimization management with a distributed asynchronous algorithm<sup>17</sup> has recently shown its efficiency to speed up complex optimizations.

Further specific research studies are being currently carried out on the validation of an adjoint method linked to a gradient-based algorithm for low-Reynolds configurations which should be the next breakthrough for blade aerodynamic optimizations on turboengines. Effectively this would lead to major reduction of the blade shape optimization time as it has been demonstrated for airplane wings over the last decade.

Finally, the introduction of robust design is launched in parallel of this optimization project that will answer to the future norm which will oblige engineers to provide a secure margin assessment for each design validation.

The future studies at Snecma detailed in the paragraph above are far from scanning all the work in progress in the field of multi-disciplinary design optimization. Others interesting ideas are described generally in Ref. 18 and in Ref. 19 which detail nearly all the promising new algorithms.

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