Aerodynamic Optimization of a Contra-Rotating Fan Investigation of Blade Number, Blade Shape and Rotational Speed Modifications

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Abstract

The present contribution fits within the framework of the VITAL project dedicated to the development of technologies aimed at reducing the perceived noise and fuel burn emissions of the new generation of civil jet engines. In this respect, one axis of investigation is the development of innovative fan designs. This paper presents several detailed aerodynamic optimizations of a counter-rotating fan. At first a description of the methodology applied to perform the aerodynamic optimizations is given. Then the CFD code and the parameterization employed are briefly presented. The performance of the design system is then demonstrated on several counter-rotating fan configurations with a different number of blades. The effect of the rotational speed is also investigated and finally some conclusions are drawn

1. Introduction

Traditionally, aerodynamic design of three dimensional blade shape is very often performed by experienced designers able to iteratively and manually modify the blade shape taking into account several results coming from aerodynamic computations (CFD) but also structural mechanics computations among others. In recent years, progress has been made in the development of automatic optimization packages able to optimize complex shapes using advanced CFD solvers and optimization algorithms [11–14].

Although these optimization methodologies are gaining acceptance in industry, they are not yet commonly used in real shape optimization. A more intensive use still requires progress in the field of automatic shape optimization. One important issue is the number of design variables that can be handled simultaneously by the automatic optimization chain. This number may indeed have to be increased from less than 10 to more than one hundred for realistic design problems. This limitation can be avoided by the use of optimization algorithms such as the one presented in this paper, based on a genetic algorithm largely accelerated by the use of an approximate model and implemented in the MAX multidisciplinary optimization software developed at CENAERO. This software has already been demonstrated to be capable of handling a large number of design variables for multidisciplinary shape optimization [15, 22].

This paper firstly focuses on the optimization methodology. Then the CFD code and the parameterization used in the design system are presented. This is followed by a brief description of the counter-rotating fan technology. The performance of the design system is then demonstrated in four different automatic aerodynamic optimizations. The two first optimizations deal with the reference configuration of the counter-rotating fan studied in the frame of the Work Package 2.4 of the VITAL project. The first optimization is a pure shape optimization. The second one considers an additionnal non geometric design parameter which is the rotational speed ratio between the 2 rows in order to investigate the effect of this parameter that is known to be of primary importance for the global fan aerodynamic efficiency. Then, the fan is optimized in 2 additional configurations: a first configuration with a reduced number of blades per row and a second configuration with an increased number of blades per row in order to investigate the effect of a variation in the blade number. Finally, some conclusions are drawn.

2. The optimizer

2.1 Genetic algorithms

The optimization algorithm developed in this research project is based on the use of genetic algorithms (GAs), which were introduced by Holland in the 70s, and improved and made well-known by Goldberg in the 80s [1]. GAs are becoming more and more widely used in mechanical and aerodynamic problems, including e.g. preliminary design of turbines [2], aerodynamic optimization using CFD [3–6], optimization of target pressure distributions for inverse design methods [7, 8], multi objective aerodynamic shape optimization [9], and multidisciplinary optimization of wing plan-form design [10].

Genetic algorithms mimic natural behavior in terms of biological evolution in order to reach the best possible solution to a given problem. Weak individuals tend to die before reproducing, while the stronger ones live longer and bear many offsprings, who often inherit the qualities that enabled their parents to survive.The working principle may be summarized as follows. An initial population is generated by selecting individuals in the whole design space. Pairs of individuals are selected from this population based on their performances (fitness/objective function values). Each of these pairs of individuals then undergo a reproduction mechanism to generate a new population in such a way that fitter individuals will spread their genes with higher probability. The children replace their parents. As this proceeds, inferior traits in the pool die out due to lack of reproduction. At the same time, strong traits tend to combine with other strong traits to produce children who perform better. The reproduction cycle is governed by a series of genetic operators, namely selection, recombination and mutation.

2.2 General strategy

Although genetic algorithms provide a very robust method, their main drawback is that they may suffer from a slow convergence because they use probabilistic recombination operators to control the step size and searching direction. As a consequence, for real industrial problems involving expensive function evaluations, the GA-required CPU time is usually impractical even with today's computing power. Therefore, a lot of effort has been put in this research project to accelerate the optimization process by exploiting an approximate model in combination with the genetic algorithm and by using robust and efficient genetic operators. The blade design algorithm is organized with the following five steps :

1. The first step consists in building a database using a design of experiments procedure (DOE). Numerous techniques exist : Full factorial, fractional, central composite, D-optimal, Latin-hypercube and random selection among others.

2. Then an approximate model is built using the design of experiments points in order to construct an analytical relation between the design variables and the simulation responses.

3. Third, an optimization algorithm is used to find the optimum using the approximate model to evaluate the objective functions and constraints.

4. Then the accurate simulation is used to evaluate and verify the real objective function and constraint values. This new simulation result is added to the database. The database is therefore always enriched with new design points, leading to an improved approximate model.

5. Go to step 2 until the maximum number of optimization cycles specified by the user is reached.

These steps are summarized in Figure 1.
More details about the method and applications can be found in References [14, 15, 17, 18, 22].

2.3 Design of experiments

In this work the design of experiments is always performed using random selection of design points improved with techniques to ensure a maximum filling of the design space. This is a generic method because it allows the user to generate a number of points independently of the number of design variables. DOE can be generated very rapidly by making use of massively parallel computers. The software developed in this research is parallelized using MPI or

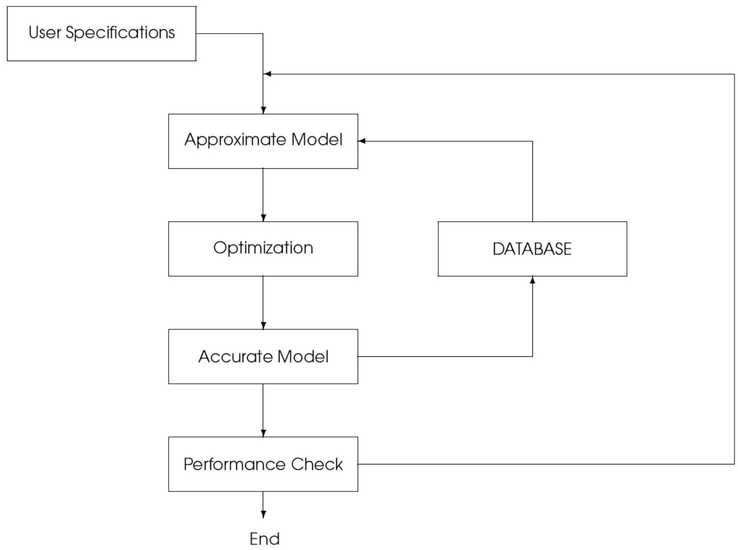


Figure 1: Flowchart of the algorithm

simply the queuing system installed on the parallel computer. In general the number of design points generated in the DOE is equal to 2 to 5 times the number of design variables.

2.4 Function approximation

Several multi-dimensional and non-linear interpolation techniques can be used to construct the approximate model, e.g. kriging, artificial neural networks, radial basis functions or lazy learning. These techniques offer the advantages of decoupling the number of free parameters with respect to the number of design parameters, which is not the case for simple polynomial interpolation. In this research, the radial basis function interpolation technique is used, mainly because of its robustness in providing a more accurate approximate model. Moreover it allows constructing a global approximate model which is valid for the entire design space. This is an important aspect for the application of the method to multiple objective optimization techniques based on the Pareto front concept, which may need information from the whole search space.

For industrial applications, the computational cost of one optimization iteration mainly depends on the cost of the simulation employed. In general the cost for building the approximate model and running the genetic algorithm is from a few seconds to a few minutes, depending on the number of training examples and the number of input and output variables.

The MAX software is parallelized meaning that several simulations can be run concurrently on several workstations and processors of a cluster. In general the number of design points generated in the initial DOE is equal to 2 to 5 times the number of design variables. More details about this method can be found in [14, 15, 17, 18].

The capabilities of this optimization techniques are demonstrated in the search for the global optimum of a multi-modal function shown in Figure 2. This figure represents the multi-modal function with only 2 design variables (the third axis being the function value), while the optimization has been performed on the same type of function but defined with 4 design variables. Figure 3 gives a close-up view of this test function in order to better visualize the local minimum.

With 4 design variables, 625 local minima are presented in the domain ranges [-10 ; 10] for every design variables.

This optimization task is first solved using the genetic algorithm alone by using a population of 50 individuals. The convergence history shows that the global minimum is found and also that only 1000 function evaluations are required.

More interesting is the result obtained by the method combining the approximate model with the GA approach. An initial database with 12 points is used and then only 100 optimization iterations are needed to find the global minimum with an accuracy of 10^{-6} (Figure 4).

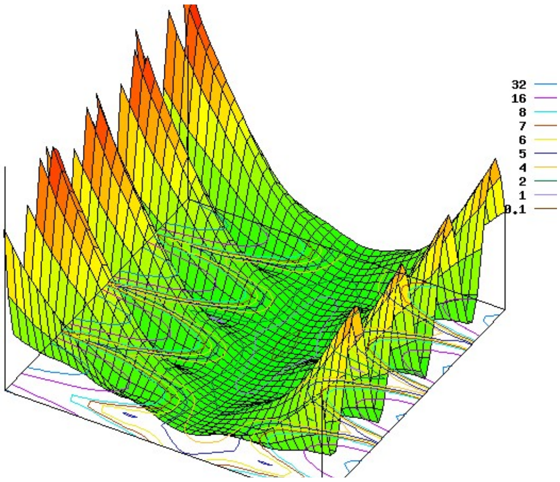


Figure 2: Multi-modal function

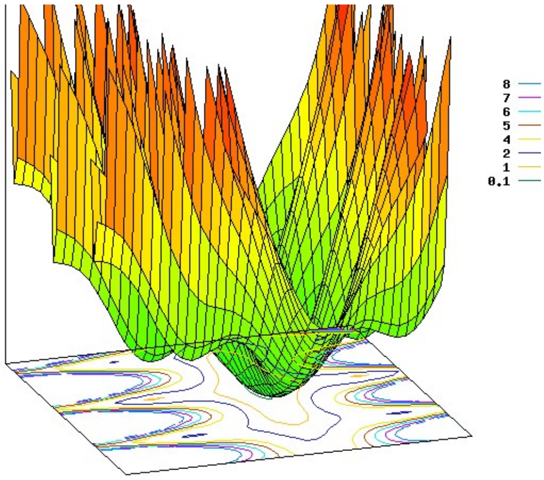


Figure 3: Zoom on the local minimum of the multi-modal function

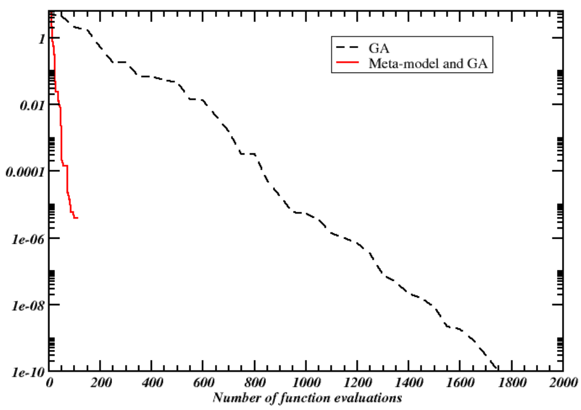


Figure 4: Convergence history on the multi-modal function

3. Flow solver and computational mesh

In the context of this work, a computational code solving the Reynolds-averaged Navier-Stokes equations (RANS) is used to predict the aerodynamic performance of turbomachinery blades. The TRAF multistage code is a three-dimensional viscous-inviscid solver developed by Andrea Arnone during a project involving ICASE (NASA Langley), ICOMP (NASA Lewis) and DEF (Department of Energy Engineering of the University of Florence) [19] and [20].

The TRAF code is able to predict the flow in linear and annular cascades as well as the flow in stationary and rotating blade passages with tip clearance. The Reynolds-averaged Navier-Stokes equations are solved using a Runge-Kutta scheme in conjunction with accelerating techniques : local time stepping, residual smoothing and Full-Approximation-Storage (FAS) multigrid. These equations are discretized using finite volumes and a cell-centered scheme with artificial dissipation. A very low level of artificial viscosity is ensured by eigenvalue scaling.

The eddy-viscosity hypothesis is used to account for the effect of turbulence. The algebraic turbulence model based on the two-layer mixing length model of Baldwin and Lomax (1978) is used to model the turbulence [21].

The solver can use either C-type or H-type grids. In this project an H-grid type is used to mesh both rotor blade passage. Both grid types can handle high stagger or high camber cascades by breaking the grid correspondence on the wake (non-periodic grid) to reduce the grid skewness in the throat region. This allows a better capture of the throat flow details such as shocks with a reasonable number of grid points. The grid generation process is based on an elliptic procedure that solves the discretized Poisson equations using a point relaxation scheme. Forcing functions are used to control the grid spacing and orientation at the wall. The three-dimensional grid is generated by stacking the two dimensional non-periodic grids.

4. Shape parameterization

The shape parameterization plays an important role in the optimization process. This is why the blade geometry modeller developed within this project pursues the following objectives, characterizing an ideal parameterization:

1. Be able to generate a large variety of physically realistic shapes with as few design variables as possible.
2. Be robust meaning that a random perturbation of the design variables should still provide a realistic blade,
3. Be able to import any existing geometries from CAD files in very little engineering time, few computational resources, and to an arbitrary accuracy specified by the designer,
4. Be generic enough to be applied to a large variety of shape optimization problems and able to be integrated or coupled with any existing CAD system,
5. Provide design variables that can easily be handled by an engineer in order to define design variable bounds,
6. Provide an easy optimization problem by minimizing the skewness and improving the conditioning of the design space.

In this study, a first step towards such a parameterization method has been achieved. The geometry is parameterized using a simple yet very efficient and generic method using control points and B-spline curves whose location are defined such as to minimize the discrepancy between the parametric definition of the blade geometry and the existing target blade shape. This methodology is general and can be applied to any curve parameterization which can therefore be used to parameterize any shape in any field. The design variables can define a modification with respect to the existing original shape or an absolute shape.

5. The counter-rotating fan technology

In line with the ACARE (Advisory Council for Aeronautical Research in Europe) objectives for 2020, VITAL aims at developing and validating engine technologies to provide a 6 dB noise reduction per aircraft operation and 7% reduction in CO_2 emissions. In this framework, the second sub-project of VITAL focuses on innovative fan designs. The Work Package 2.4 investigates on the counter-rotating fan technology, which is one of the most promising new technologies. It enables higher pressure ratio in a few stages, lower fan tip speed and therefore decreased noise level, higher BPR, and reduced engine weight. The design of a CRF presents a very challenging test case for the optimization framework for several reasons:

- The blade shape of aero-engine fans is becoming more and more three-dimensional in order to optimize aerodynamic performance.

- The optimal solution depends on both rotor blade shapes, leading to a larger number of design variables for the optimization process.
- The computation is challenged by the sensitivity of the rotors due to high Mach numbers, strong shocks, and high loading that can lead to boundary layer separation and breakdown of the CFD flow solver.
- Moreover, the aerodynamic performance of the CRF strongly depends on design variables, such as the independent rotor speeds and blade counts, in addition to the large number of geometrical parameters required to capture subtle shape changes required in supersonic blades.

6. Aerodynamic optimizations

The aeroynamic design is performed by solving a mono-objective constrained problem (only inequality constraints are imposed) which can be formulated mathematically as:

$$min_{\mathbf{x}} f(\mathbf{x}) \text{ with } \mathbf{x}^T = (x_1 \ldots x_n) \text{ and } \overline{X_i} \geq x_i \geq \underline{X_i} \ \forall i = 1 \ldots n$$
$$\text{such that}$$
$$g_j(\mathbf{x}) \geq 0 \ \forall j = 1 \ldots p$$

The objective function is the inverse of the adiabatic efficiency at the considered operating point (defined by equation (1), π_{op} and τ_{op} are respectively the total pressure ratio and the total temperature ratio) while three inequality constraints are imposed (i.e. $p = 3$). The first one is imposed to prevent the optimizer from looking for geometries which are more prone to stall. In practice, a stall margin value is evaluated from the performance curves and a lower bound is imposed on this margin. The two other constraints imposed are a lower and an upper bound on the mass flow. The latter ensure that the mass flow at the considered operating point for the different geometries evaluated along the optimization process is kept close to the mass flow of the original geometry by the optimizer.

As the operating point and the stall margin are to be determined thanks to the performance curve, at each iteration within the optimization process five different CFD computations are perfomed on the same geometry with five different outlet pivot static pressures imposed at the hub (the pressure in the whole outlet plane is then computed thanks to a simplified radial equilibrium condition). With these five points, the performance curve for the total pressure ratio and the efficiency can be constructed thanks to a B-spline interpolation. The considered operating point mass flow is then located at the intersection between the operating flight line (a priori known) and the total perssure ratio performance curve.

$$\eta_{op} = \frac{\pi_{op}^{\frac{\gamma-1}{\gamma}} - 1}{\tau_{op} - 1} \tag{1}$$

The objective function and constraints defined above might be very nonlinear. The general approach to this kind of problem is to transform the original constrained minimization problem into an unconstrained one by converting the constraint into penalty terms that are increasing when violating the constraints. The optimizer tries to minimize the pseudo-objective function $f^*(X)$ defined by (2):

$$f^*(X) = \frac{f(X)^2}{f_{ref}} + \underbrace{\sum_{j=1}^{p}}_{g_j(X)<0} \frac{(g_j(X))^2}{g_{j_{ref}}} \tag{2}$$

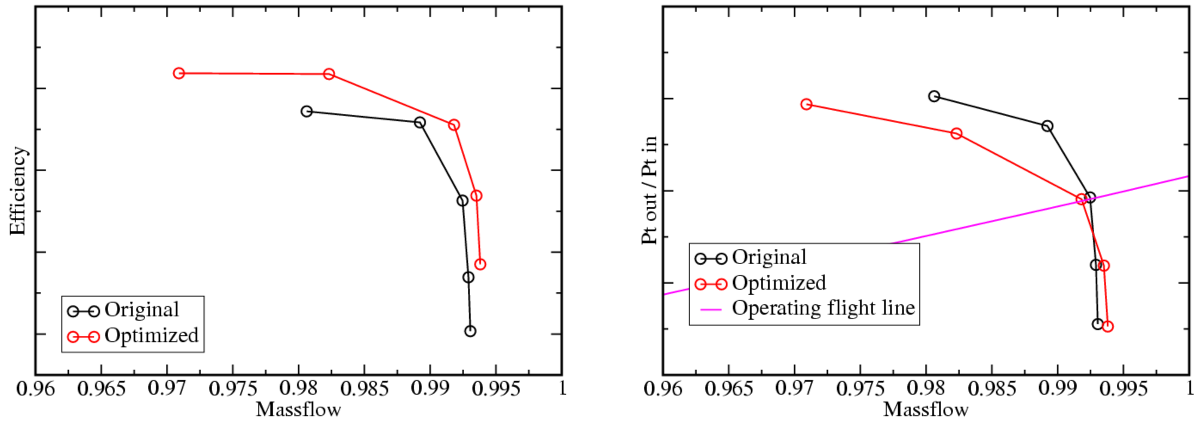
In the following sections, three different configurations have been optimized. The first one is the baseline configuration that consists of 10 blades for the first rotor and 14 blades for the second one. On this first configuration, two different optimizations have been performed. The first one solely deals with geometric design variables while the second one additionally includes the rotation speeds ratio in the set of design variables. Then, two other optimizations have been perfomed on two configurations respectively with a decreased and an increased number of blades in order to investigate the effect of the blade number on the aerodynamic performances of the counter-rotating fan.

In all the performance curves presented in the following the massflow has been adimensionalized. The distance between two consecutive ticks on the y axis corresponds to an increase of 1 % for what concerns the efficiency and of 0.025 for the pressure ratio.

6.1 First optimization results

As already mentioned, this optimization only involves geometric design variables and three inequality constraints are imposed: a lower bound on the stall margin and an upper and lower bound on the massflow to keep it close to the mass flow of the original geometry. The performance curves are shown in Figure 5(a) and Figure 5(b). The optimization leads to an increase of 2.32 % of the isentropic efficiency at the considered operating point. As far as the pressure ratio is concerned it is kept close to its initial value at the considered operating point.

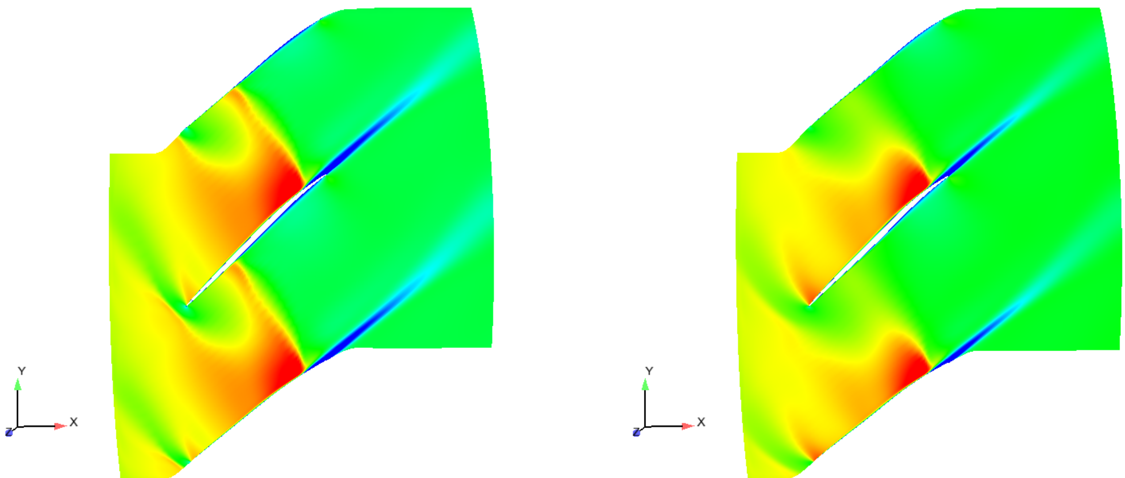
Figure 6(a) and Figure 6(b) depict the relative Mach number at 95 % span for the second rotor at the considered operating point respectively for the original blade and for the optimized blade. These pictures clearly show the downstream shift and the weakening of the shock structure, which leads to the improvement of the aerodynamic efficiency of the counter-rotating fan highlighted in Figure 5(a).



(a) Efficiency

(b) Total pressure ratio

Figure 5: Comparison between original and optimized geometry performance curves (optimization 1)



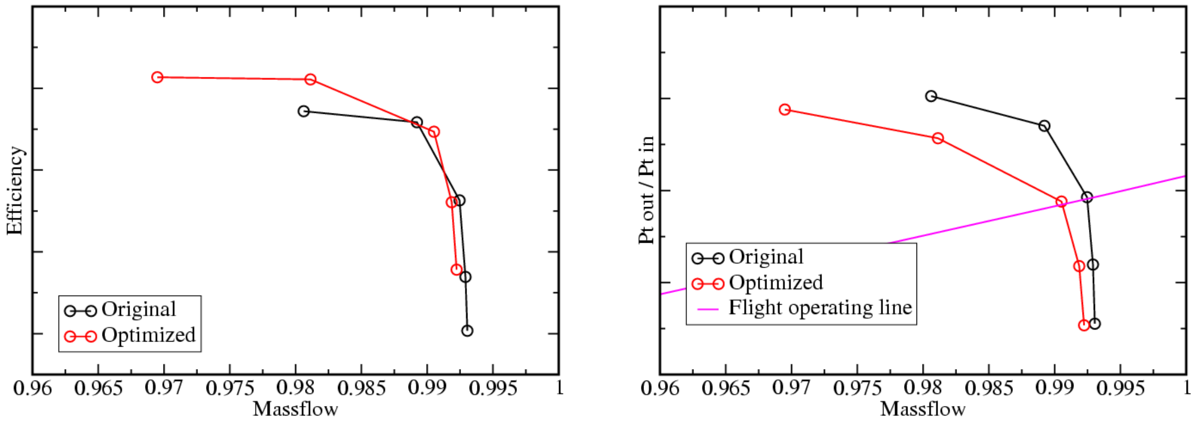
(a) Original

(b) Optimized

Figure 6: Comparison of the relative Mach number distribution in a blade-to-blade surface at 95 % span of the second rotor between the original and optimized geometry (optimization 1)

6.2 Second optimization results

For the second optimization, the same original configuration is considered, the objective function and constraints are the same but an additional non geometric design variable is considered. The latter is the ratio between the rotation speeds of the two rotors. Because of the additional design variable taken into account during the optimization, it would have been expected to obtain an isentropic efficiency gain higher than the one obtained in the previous optimization case. However, an isentropic efficiency gain of 2.12 % was achieved in the present case while a gain of 2.32 % had been obtained with the first optimization, without the additional rotational speed design variable. This may be attributed to the fact that the addition of this new design variable makes the optimization problem much more difficult. The additional variable seems to create a very narrow valley in the optimization path, which increases the difficulty to find the optimum and possibly creates additional local minima. Further investigation of this problem would be interesting with a larger DOE. The performances curves obtained are displayed in Figures 7(a) and 7(b).



(a) Efficiency

(b) Total pressure ratio

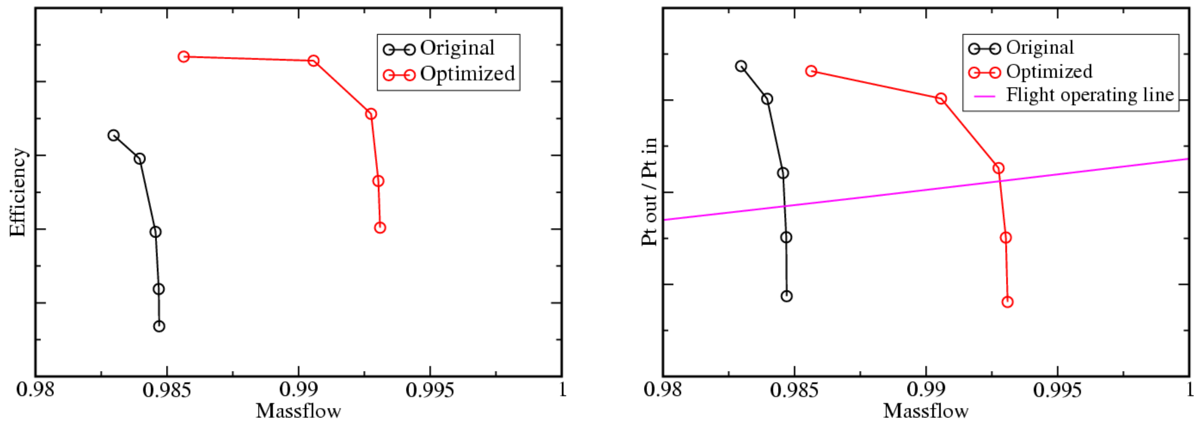
Figure 7: Comparison between original and optimized geometry performance curves (optimization 2)

6.3 Third optimization results

In the frame of this third optimization, a new configuration with a reduced number of blades per row is considered. The new original configuration is obtained by applying a scaling procedure to the baseline geometry. Let us emphasize the fact that, compared to the baseline configuration, the new one cannot be considered as an initial design and as a matter of fact leads to lower performances as far as the initial geometry is concerned. As can be seen in Figure 8(a), an improvement of the isentropic efficiency of about 2.7% is achieved at the considered operating point. The total pressure ratio is also slightly increased, but these improvements come with a larger mass flow.

6.4 Fourth optimization results

In the frame of this fourth optimization, a configuration with an increased number of blades per row is considered. Once again, this new configuration is obtained by applying a scaling procedure to the baseline geometry and, since this new configuration cannot be considered as an initial design, it leads to lower performances with respect to the original configuration. As can be seen in Figure 9(a) and Figure 9(b), the optimization procedure leads to an isentropic efficiency improvement of about 0.73% at the considered operating point only. The total pressure ratio also appears slightly increased at this point. In order to understand this poorer isentropic efficiency gain with respect to the previous optimizations conducted, it must be underlined that the mass flow constraints aim at keeping the mass flow at the considered operating point for any geometry along the optimization process close to the mass flow obtained with the initial geometry and configuration. The scaling applied to obtain the increase number of blades configuration however

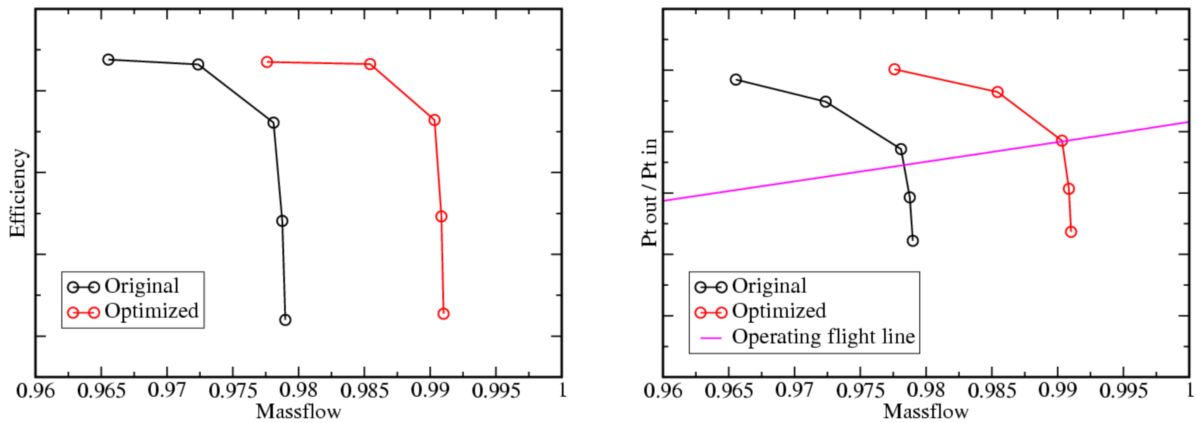


(a) Efficiency

(b) Total pressure ratio

Figure 8: Comparison between original and optimized geometry performance curves (optimization 3)

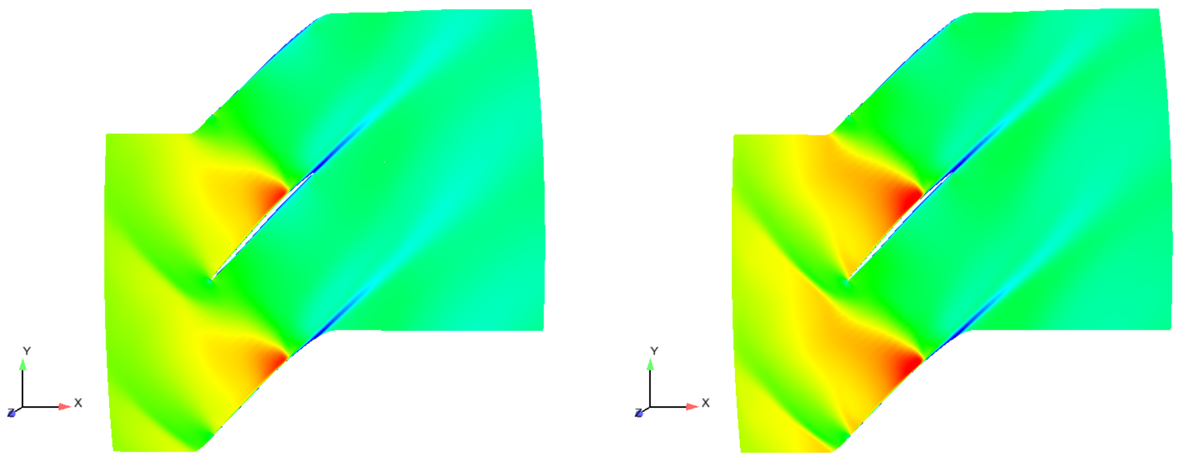
is such that when the flow is computed at the same operating point for this new configuration, it leads to a quite smaller mass flow compared to the one obtained for the initial configuration. Considering equation (2), it is clear that the penalty associated with the violation of the lower bound on the mass flow might master the first term of (2) related to the adiabatic efficiency in the global objective function. As the penalty is quite large, the easiest way for the optimizer to reduce the global objective function is to reduce the penalty i.e. increase the mass flow. Compared to the first configuration optimization, Figures10(a) and 10(b) do not demonstrate an important change in the shock structure with a strength decrease which would have a positive impact on the efficiency.



(a) Efficiency

(b) Total pressure ratio

Figure 9: Comparison between original and optimized geometry performance curves (optimization 4)



(a) Original

(b) Optimized

Figure 10: Comparison of the relative Mach number distribution in a blade-to-blade surface at 95 % span of the second rotor between the original and optimized geometry (optimization 4)

7. Conclusions

The goal of the present contribution within VITAL WP 2.4 was to improve the efficiency of a counter-rotating fan with constraints on mass flow and stall margin. Along the different optimizations conducted, the effect of blade number variation and second rotor speed variation have been investigated for both design and off design conditions. The conclusions that can be drawn may be summarized as follows:

- The highest efficiency is obtained with the configuration with the original number of blades
- No further improvement could be obtained with a variation of the speed of the second rotor in addition to the blade shapes variables, at least in the range examined and with the same DOE as for the pure blade shape optimizations
- The highest improvement in isentropic efficiency is obtained for the configuration with the smallest number of blades which allows even to reduce the manufacturing cost
- The smallest improvement in isentropic efficiency is obtained for the configuration with the higher number of blades, which also yields the higher manufacturing cost
- The configuration with the original number of blades is the only one that performs better even at off design conditions

These conclusions point out the configuration with the original number of blades and the configuration with the reduced number of blades as the most promising ones.

Acknoledgements

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