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Improved aerodynamic design of turbomachinery bladings by numerical optimization ☆

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Abstract

The aerodynamic optimization of a transonic compressor is reported in this paper. The Q3D Navier–Stokes solver COLIBRI is coupled to a gradient-based method (CONMIN) and to a genetic algorithm (GADO). The suction side of a 2D blade is optimized by using both optimization methods with a significant efficiency improvement. In 3D, the performance improvement is obtained by modifying the suction surface of a transonic compressor with a Bézier surface and by using the CANARI solver coupled to the gradient method (CONMIN).

Résumé

L'optimisation aérodynamique d'un compresseur transsonique est présentée dans ce papier. Le solveur Navier–Stokes quasi-3D COLIBRI est couplé à une méthode du gradient (CONMIN) et à un algorithme génétique (GADO). L'extrados de l'aube 2D est optimisé en utilisant ces deux méthodes, avec une augmentation significative du rendement. En 3D, l'amélioration de performance est obtenue en modifiant l'extrados d'un compresseur transsonique par une surface de Bézier et en utilisant le solveur CANARI couplé à la méthode du gradient (CONMIN).

Keywords: Turbomachinery; Optimization; Compressor; Gradient; Genetic; Bézier

Mots-clés : Turbomachine ; Optimisation ; Compresseur ; Gradient ; Génétique ; Bézier

1. Introduction

Engine manufacturers are steadily asking for higher performance in terms of efficiency, pressure ratio or mass flow of the different components of the engine (rows, stages, ...). This will leads to the use of CFD in an intensive way for turbomachinery blade design [9] but this higher performance must be achieved within shorter design cycles and at lower cost. Traditionally, CFD has been used in an analysis mode for cut-and-try approaches to design, with eventually a large scattering of the results. The recent progress of the CFD code performance (reduced CPU time, better accuracy, improved reliability) enable to reduce the design time by coupling CFD codes with optimization tools. This can be applied both in Q3D and 3D, with various optimization and blade deformation techniques.

This paper describes the performance improvement of a transonic compressor blade computed both with a Q3D and a 3D approach. All CFD calculations are carried out with a Navier–Stokes solver. The goal of the optimization is to achieve maximum efficiency at a given operating point (pressure ratio, mass flow). In the Q3D approach, a gradient-based method is used for a first optimization and is compared to the optimization result obtained with a genetic algorithm. The suction side of the blade is modified by applying a deformation function defined by a Bézier curve which control points are positioned by the design variables. The overall efficiency is increased by more than two points in both cases. Moreover, the optimized blading shows a significant improvement of performance both at the design and at off-design points. In the 3D approach, the gradient-based method is used. The suction side of the blade is modified by applying a deformation function defined by a Bézier surface. The efficiency improvement is greater than one point after only three optimization cycles.

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Nomenclature

$y_i, y_{i,j}$	design variables	m	degree of the Bézier in the v direction
$\xi_i, \xi_{i,j}$	position of design variables (% chord)	$\vec{P}_i, \vec{P}_{i,j}$	control point
$\eta_{i,j}$	position of design variables (% span)	$\eta_{\text{isentropic}}$	isentropic efficiency
nv	number of design variables	Q_m	mass flow kg/s
nc	number of constraints	Rp_i	total pressure ratio
$\vec{G}$	constraints vector	Rt_i	total temperature ratio
F_{obj}	objective function	α	absolute flow angle
u, v	Bézier curve parameter	β	relative flow angle
ξ	reduced chord	V_n, V_{t1}, V_{t2}	norm. and tangt. velocities
η	reduced span	p	static pressure
δ	local deformation	ρ	density
B_k^n	Bernstein polynom	H_i	total enthalpy
n	degree of the Bézier in the u direction	ds	local surface

2. Optimization procedure

As shown in Fig. 1, the optimization strategy is composed of four main parts. The optimization algorithm supplies a set of design variables to the grid deformation tool which propagates deformations and generates a new mesh. The aerodynamic field is updated by calling a steady Navier–Stokes code (both for Q3D and 3D). The objective function and constraints are then deduced from the flow results by integration of the flow solution downstream of the blading.

2.1. Numerical optimization

The gradient-based method used here is CONMIN [16, 17]. The aim is to define a vector of design variables $\vec{y} = (y_1, y_2, \ldots, y_{nv})$ which minimizes a scalar objective function $F_{\text{obj}}(\vec{y})$ with constraints $\vec{G}(\vec{y}) = (g_1, g_2, \ldots, g_{nc})$. The constraints are violated if $\vec{G}(\vec{y}) > 0$. In the present methodology, all gradients are determined by finite differences at each optimization iteration. For the first iteration, the gradient is taken as $\vec{S}_q = -\vec{\nabla} F_{\text{obj}}(\vec{y})$. For the following iterations, the gradient depends on the constraints. If the constraints are violated, $\vec{S}_q$ is given by the feasible direction method of Zoutendijk. Else, $\vec{S}_q$ is calculated by the Fletcher and Reeves conjugate gradient method. In the iterative process, the design variables vector is given in function of the one from the previous calculation by the relation $\vec{y}^{n+1} = \vec{y}^n + \alpha \vec{S}_q$ where α is the displacement modulus to be applied in the $\vec{S}_q$ direction. This α modulus is evaluated by a polynomial approximation. At each iteration, three steps are performed to search for the objective function minimum and to respect the constraints. In summary, for nv design variables, the n iteration optimization process requires $1 + n(nv + 3)$ calls to the solver.

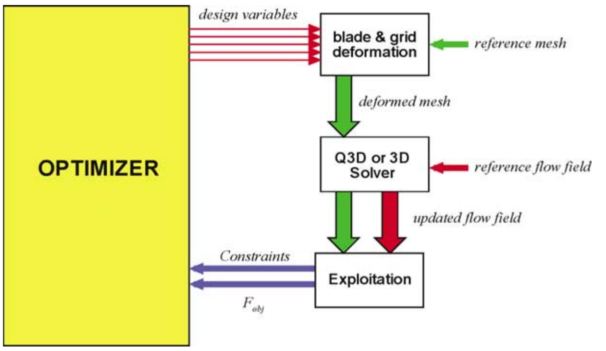

Fig. 1. Optimization flow chart.

GADO [2,14], which is the acronym for Genetic Algorithm for Design Optimization is a stochastic optimizer. It first generates a random population of potential candidates. Then mutations and crossovers are applied to individuals of the population in order to make the population evolve towards better solutions. Compared to classical Genetic Algorithms, several improvements have been included that make the search more efficient and reliable for engineering problems. Each individual is represented by a vector of real numbers, which is particularly well adapted to the parametric description of a shape. Several innovative crossover and mutation operators have been developed in order to make the search process fast and accurate, i.e., more likely to find the global optimum. Depending on the number of iterations allowed for the search, the stage of the optimization process is taken into account. For example, a guided crossover operator (which mimics a gradient-based method) is applied in the last part of the search, with a view to accelerate the convergence. The shape of the population is also checked to detect premature clustering and a reseeding of the population can be performed in order the avoid the search process to be stuck near a local optimum of the design space. Finally, constraints are described by applying a penalty coefficient on the objective function.