Numerical Optimization of the Turbine Blade Leaning Angle Using the Parallel Genetic Algorithm

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Abstract

The leaning angle optimization of turbine blade using the genetic algorithm was conducted in this paper. The calculation CFD technique was based upon the Diagonalized Alternating Directional Implicit scheme(DADI) with algebraic turbulence modeling. The leaning angle of VKI turbine blade was represented using B-spline curve. The control points are the design variable. Genetic algorithm was taken into account as an optimization tool. The objective was to minimize the total pressure loss. The optimized final geometry shows the better aerodynamic performance compared with the initial turbine blade.

Introduction

Improvement of aerodynamic performance of a turbomachinery blade requires a correct tailoring of the velocity distribution along its wall. The velocity distribution determines the aerodynamic load and the behavior of the viscous layers in which originates the losses. Most designers still adopt a direct approach for tailoring: they evaluate the performance of the actual geometry using numerical and/or experimental tools, and they modify it according to empirical rules or to their own experience. This approach can be very time consuming, and turn out to be an unefficient in some cases. It is clear now that more powerful design strategies can only be obtained.

Optimization techniques use numerical analysis tools as black boxes and replace the designer by a systematic calculation of the sensitivity of the performance to geometrical parameters. In this approach, a set of geometrical parameters is iteratively modified until the best combination is found, which minimizes a certain objective function. The cost of such a process is still so high that the flow solvers are based on cheap models or that the number of parameters used to define the geometry is drastically restricted. The major advantages of optimization methods rely on the capability to find a solution even if the required performance is partly unrealistic although most of these methods can not guarantee that the true minimum is reached. Specially the aerodynamic characteristics is highly non-linear so that gradient search algorithm can hardly escape from the local minima. However the non-gradient search algorithm is still expensive for geometry optimization.

More recently, due to the development of computer hardware and software researchers have begun to pay attention to the genetic algorithm as an aerodynamic shape optimization tool. For example, Takanashi and Obayashi (1) optimized the target pressure distribution using a genetic algorithm. Once they achieved the target pressure distribution, an inverse method was applied to get the corresponding geometry. Yamamoto and Inoue (2) solved the aerodynamic shape optimization problems by means of genetic algorithm with a compressible Navier-Stokes solver. Madavan *et al*. (3) optimized a turbine airfoil shape using neural network algorithm and the unsteady Navier-Stokes solver by Rai (4).

The major problem in shape optimization using a non-gradient search algorithm (Genetic Algorithm, Simulated Annealing and Neural Network) and a CFD solver, is due to its heavy CPU load. They usually require the several hundred times of CFD runs. It takes about a couple of weeks which the most designers can hardly handle. However, the non-gradient search algorithm can escape the local minima, which is desirable for most aerodynamic problems. That is the reason why the CFD people prefer to use the non-gradient search algorithm such as a genetic algorithm even though its heavy computational time.
This paper describes the implementation of the optimization technique based upon the genetic algorithm and CFD for turbomachinery blade design. To reduce the heavy computational time, the parallel computing algorithm is introduced.

To improve the aerodynamic performance of a turbine blade, the leaning angle (dihedral angle) of the stacking axis is often modified in modern turbomachinery. The leaning angle variation along the span changes the flow-field normal to the streamwise direction. The secondary flow-field, the shape and strength of horseshoe vortices are influenced by the blade leaning angle. Here, an optimization of the leaning angle variation of turbine inlet guide vane will be performed by genetic algorithm in this research.

Numerical Algorithm

Flow Solver

The computer code solves the Reynolds averaged Navier-Stokes equations. It is based on the Diagonalized Alternating Direction Implicit (DADI) scheme (5), with the k-ε (6) turbulence modelling. Considering the flow is supersonic, the compressibility effect suggested by Nichols (7) was also added in the turbulence modelling.

A hybrid H-type grid was generated to discretize the computational domain. The hybrid grid generation method consists of the following two procedures. First, the initial grid was generated by a transfinite interpolation method. Second, due to the lack of grid smoothness, an elliptic differential operator was applied to the initial grid. Non-matching grid was used along the periodic line.

The inlet total pressure was 208548 Pa and the total temperature 278 K. The static pressure at exit was 110172 Pa and the exit flow was sonic (***M***exit=1.0). The radius of shroud was 455 mm and hub radius was 405 mm. The number of blades in the stator was 82. To discretize the physical domain, an H-type (129x34x33) grid was generated by transfinite interpolation.

Optimization

The VKI airfoil was chosen as the base airfoil shape. The blade stacking axis described the circumferential position of the airfoil as a function of radial position. The VKI airfoils were stacked from root to tip according to the shape of the stacking axis. Different stacking axis shapes resulted in different blade shapes. The goal here is to find a shape of the stacking axis that result in the most efficient blade for a fixed airfoil shape. In this case, the most efficient blade was considered to be the blade with the lowest total pressure loss.

The stacking axis was parameterized with a B-spline with 5 control points. Each variable corresponding to each control points was discretized with a 6-bit binary string. A population of 31 was used with a 6% probability of mutation and a 50% probability of uniform crossover.

Constraints are treated as a penalty during the optimization. A single CFD run requires about three or four hours. When twenty generations are required during one optimization, 600 CFD runs are needed. If single CPU machine runs, it takes about three months per one optimization. To reduce such a heavy CPU load, a parallel genetic optimizer was introduced. The machine used in this study is composed of 32 nodes, each with two Intel Pentium IV 1.7 GHz CPU's and 512 MB of SDRAM. One optimization takes about three days in parallel machine.

CPU time of parallel GA = Population size × CPU time of one CFD run × No. of generations / No. of processors

Objective function	**Minimize** $\dfrac{P_{t\ inlet} - P_{t\ outlet}}{P_{t\ inlet}}$
Constraints	$\dot{m}$ **(mass flow rate) = constant**
Design Variables	**5 control points for B-spline**

Table 1 Formulation of turbine blade leaning angle optimization

Calculation Results

The initial blade has the VKI airfoil and the straight blade span. There is no blade tip because of the stator. However, the flow field in hub region is different from the flow in tip region. During the optimization, the population size of each generation set to 31 because the parallel machine has 32 CPU processors. About 20 generations has passed, convergent solution can be reached.

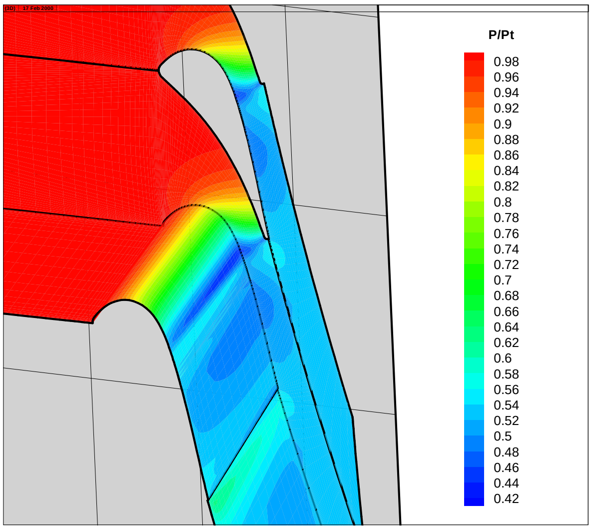

Figure 1 Pressure contours of VKI stator blade (Mexit=1.0, straight, initial)

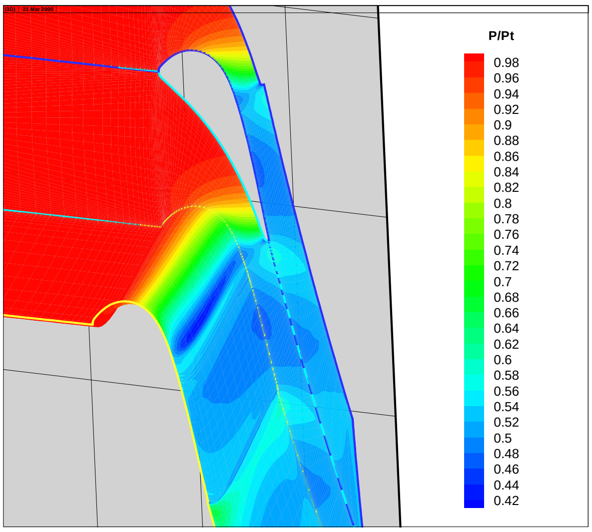

Figure 2 Pressure contours of VKI stator blade (Mexit=1.0, leaned, optimized)

Figure 1 represents the static pressure contours on the hub and blade surfaces. At inlet, the total pressure keeps in its inlet value. The total pressure decrease as the flow pass through the blade until it reaches the throat. The weak normal shock was generated at the throat. The throat corresponds to the lower region of the trailing edge. The pressure peak at the blade tip is lower than the peak at hub due to the difference in radius. Therefore the pressure gradient at the shock region becomes weaker at the tip region than at the hub region. The wake from the trailing edge has been developed along the center of blade pitch.

The static pressure contours of the optimized leaned blade are shown in Figure 2. The peak pressure band on the blade surface is wider and thicker than on the straight blade. It means that the lower pressure region becomes larger in the optimized blade than in the initial straight blade.

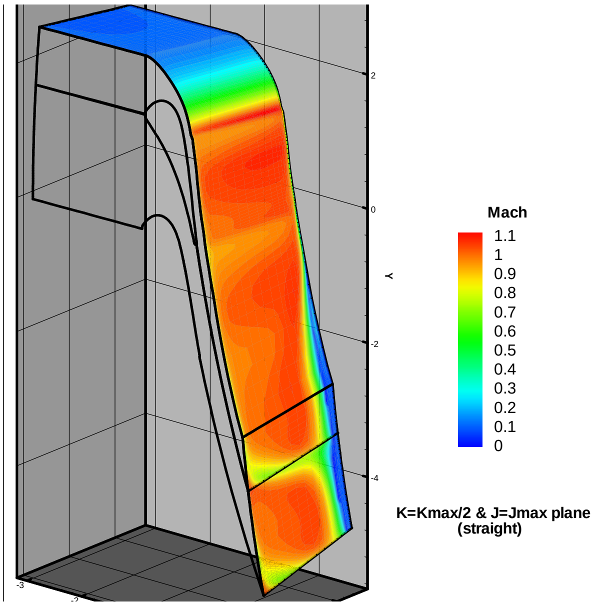

Figure 3 Mach contours at a half pitch and exit planes (Mexit=1.0, straight, initial)

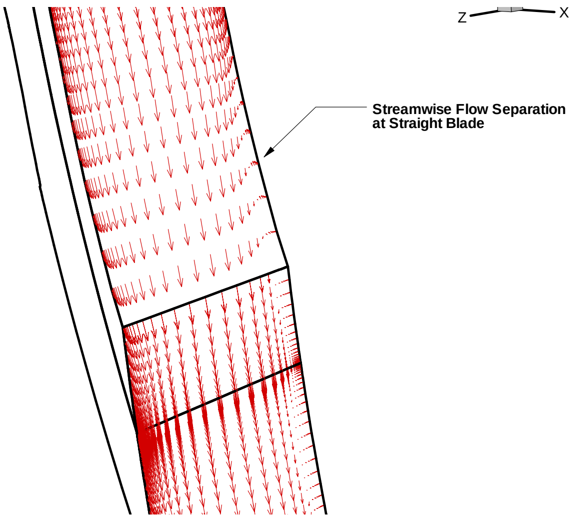

Figure 4 Velocity vector plot at a half pitch and exit planes (Mexit=1.0, straight, initial)

Figure 3 illustrates Mach contours at K=Kmax/2 and J=Jmax planes in computational domain. J index corresponds to the streamwise direction and K index to the surface normal direction. At the exit plane(J=Jmax), the dark blue band, which corresponds to very low Mach number can be seen at the hub region. This low Mach number region indicates the flow separation due to the curvature effect at hub. The convex wall at hub induces the adverse pressure gradient, which results in flow separation. However, the concave wall at the shroud induces the favorable pressure gradient. Thus, flow separation does not occur at the shroud region. This flow separation can be seen more clearly in Figure 7.

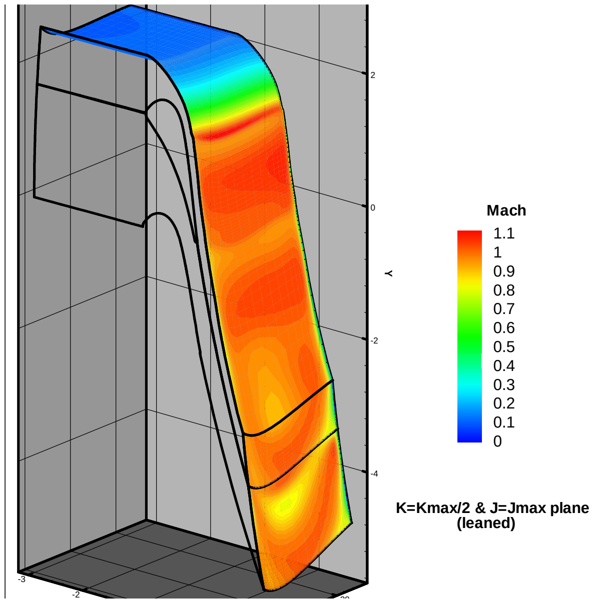

Figure 5 Mach contours at a half pitch and exit planes (Mexit=1.0, leaned, optimized)

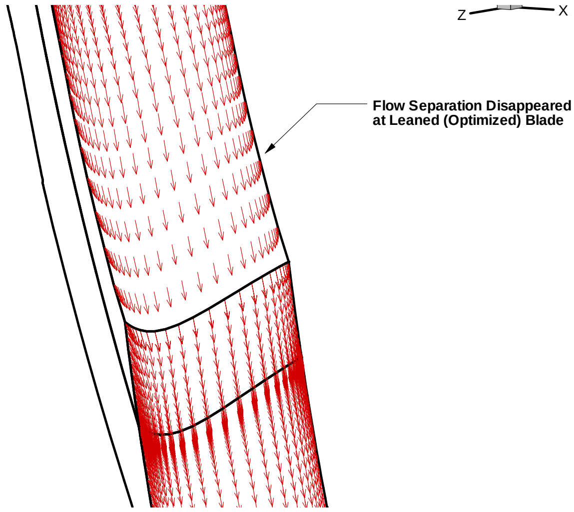

Figure 6 Velocity vector plot at a half pitch and exit planes (Mexit=1.0, straight, initial) leaned, optimized)

The optimized lean angle distribution blade illustrates the different Mach contours at the exit plane in Figure 5. First, the wake sheet becomes highly stretched because of the leaning angle. Second, the low Mach number band (dark blue in Figure 3) has been removed. It means that no flow separation occurred at this blade and velocity vectors at hub are successfully developed (Figure 8). Therefore, less total pressure loss should occur in the leaned blade.
The Mach number contours at the exit plane are shown in Figures 7 and 8. The geometry of leaned blade can be seen in Figure 8. At the hub region, the leaning line tilted towards the counter clockwise direction. This effect causes the acceleration of the flow near the hub region and retards the flow separation.

Considering that the pressure at the exit plane is constant, the small Mach number means the small total pressure value. The large pressure loss region in straight blade (dark blue band at hub) has been removed at the optimized blade.

The integrated total pressure loss reduction in this optimization test case was 3 %. Typical values of experimentally measured total pressure loss reduction for blades with non-optimized leaned stacking axis are about 2 %.

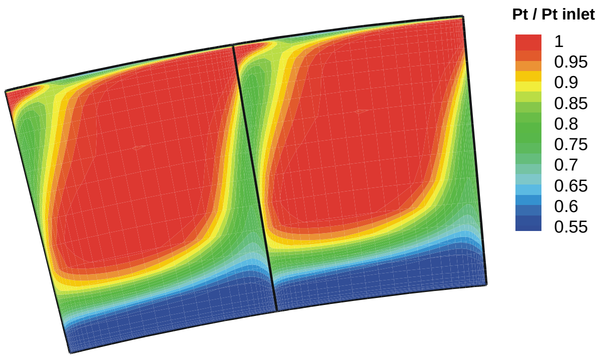

Figure 7 Mach contours at the exit plane (*M*exit=1.0, straight, initial)

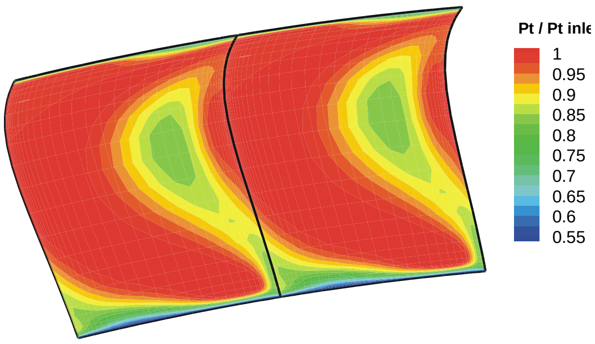

Figure 8 Mach contours at the exit plane (*M*exit=1.0, leaned, optimized)

Conclusions

In this research, numerical optimization of turbine blade leaning angle was attempted. The change of the blade leaning angle causes the variation of secondary flow fields. Therefore, flow solver should be three dimensional. Due to the non-linear characteristics of aerodynamic behavior, the non-gradient search algorithm was preferred. The numerical calculation of the three dimensional flow-field and the selection of genetic algorithm make the computational load to be heavy. To reduce the load, parallel computing was successfully adopted.

The flow separation has occurred at the hub region in the initial blade because of the radius effect. The flow separation causes the large total pressure loss, which is undesirable. The final optimized leaned blade does not have flow separation and the total pressure loss was decreased about 3% which compared with the initial blade. This approach proves to be robust and efficient tool in turbomachinery design.

References

1) Obayashi, S.: Freestream Capturing for Moving Coordinates in Three Dimensions, *AIAA Journal*, Vol.30, No.4, pp.1125-1128, June 1991.
2) Yamamoto, K. and Inoue, O.: Applications of Genetic Algorithm to Aerodynamic Shape Optimization, AIAA-95-1650-CP, 1995.
3) Madavan, N. K., Rai, M. M. and Huber, F. W.: Neural Net-Based Redesign of Transonic Turbines for Improved Unsteady Aerodynamics Performance, 35th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, June 20-24, 1999, Los Angeles, CA
4) Rai, M. M. and Madavan, N. K.,: Multi-Airfoil Navier-Stokes Simulations of Turbine Rotor-Stator Interaction, *Journal of Turbomachinery*, Vol. 112, pp. 167-190, 1990
5) Steger, J. L.,: Implicit Finite-Difference Simulation of Flow About Arbitrary Two-dimensional Geometries, *AIAA Journal*, Vol. 16, No. 7, pp. 679-686, July 1978.
6) Chien, K.-Y.,: Prediction of Channel and Boundary-Layer Flows with a Low Reynolds Number Turbulence Model, *AIAA Journal*, Vol. 20, pp. 33-38, 1982
7) Nichols, R. H. : Development and Validation of a Two-Equation Turbulence Model with Wall Function for Compressible Flow, AIAA-90-2385-CP, pp. 115-129, 1996