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SHAPE OPTIMIZATION OF TYPICAL HEAVY-DUTY GAS TURBINE COMPRESSOR AIROFOIL USING METAMODEL BASED ALGORITHM

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Abstract
For design optimization with high-dimensional expensive problems, an effective and efficient optimization methodology is desired. This work proposes a new metamodel-based approach for the shape optimization of a typical heavy-duty gas turbine compressor airfoil. The proposed methodology is called Approximated Promising Region Identifier (APRI), which is a global optimization algorithm based metamodeling techniques. The shape of turbine compressor airfoil is optimized with the objective of minimizing the total pressure losses for the design condition as well as maximizing the airfoil operating range. Design optimization is carried out by coupling geometry parameterization of the airfoil shape, a blade-to-blade flow analysis in CFD module of COMSOL Multiphysics, and a developed APRI in MATLAB script as the optimization algorithm. Using the combination of these adaptive tools and methods, the preliminary results are considerably promising in terms of computation time, number of function evaluations, and the airfoil shape performance enhancement. The obtained results are compared with Genetic Algorithm (GA) to highlight the advantages of using the metamodel-based optimization algorithm for real-world complex engineering problems such as aerodynamic shape optimization problems in the turbomachinery field.

Keywords: Airfoil geometry, gas turbine compressor, optimization, metamodeling

1. Introduction

Engineering optimization algorithms are used extensively nowadays to optimize complex real life engineering applications. Shape optimization of complex mechanical systems represents one of the challenges that require efficient and robust optimization algorithms. In this paper, shape optimization methodology for a typical heavy-duty gas turbine compressor rotor blade sections is presented and modified. The approach presented here combines a Non-Uniform Rational B-Spline (NURBS) [1] driven parametric geometry description, a two-dimensional flow analysis, and a meta-model optimization algorithm known as approximated promising region identifier (APRI), which is a modified version of space exploration of uni-modal region elimination (SEUMRE) [2], developed specifically for this purpose and can be used to optimize other engineering optimization problems.

Since the use of evolution-based techniques in combination with CFD analysis tools for solving optimization problems in turbomachinery aerodynamics is limited by the massive computational effort, applying surrogate assisted algorithms seems to be a useful alternative. The genetic algorithms, for example, need too many CFD evaluations for convergence, which is not acceptable especially for expensive objective functions evaluation in aerodynamic shape optimization. Hence because of most of the computational time is spent in the evaluation of the objective function, a faster solution approach would be more appropriate.

The aerodynamic design optimization techniques for turbomachinery application have dramatically changed in the last years. While traditional 1-D and 2-D design procedures are consolidated for preliminary calculations, emerging techniques have been developed and are being used almost routinely within industries and academia.

The compressor/turbine blade design remains a true challenge as it is a very complex and multidisciplinary task, where aero/thermodynamic issues, which traditionally considered prevalent, has now become part of a more general design approach, where multidiscipline concerns such as aeromechanical, technological, structural, noise-related and many other matters have to be taken into account simultaneously, thus making the designers jobs more challenging and complex. Although designer experience plays a major role, the complexity evidenced above

demands for a more structured and organized way of handling the problem, where mathematical and statistical tools are implemented and used in the decision making process.

Nowadays, interesting and alternative options are in fact available for compressor design, such as new blade shapes for improved on/off design efficiency, end wall contouring and casing treatments for enhanced stall margin, and many others. For this reason, while experimental activity remains decisive for ultimate assessment of design choices, numerical design optimization techniques, along with Computational Fluid Dynamics (CFD) are assuming more and more importance for the detailed design and concrete evaluation of options. Engineering optimization is becoming an essential factor in the design of turbomachinery blades. Also, meta-model based optimization methods enable the solution of optimization problems demanding substantial computation resources. Thus, meta-model-based optimization algorithms have found a huge interest and success in the turbomachinery filed and specifically in the optimization of turbine and compressor blades.

The proposed APRI method works by exploring the whole design space by sending agents (sampling points) to explore the design space. Based on the information obtained from all agents, the algorithm focuses the search in the most promising region by deploying more agents to explore the region (generating more sample points). Latin Hypercube Design (LHD) [3], which is a well-known sampling technique, is used as a sampling technique to generate sample points. Once a promising region is identified, this region is refined by more sample points. A surrogate model or meta-model is then constructed to mimic the expensive objective function and help in searching for optimum solutions. With the objective of minimizing the total pressure losses for the design condition as well as maximizing the airfoil's operating range, design optimization is carried out by coupling an established MATLAB code for the geometry parameterization of the airfoil shape, a blade-to-blade flow analysis in CFD module of COMSOL Multiphysics, and a developed APRI in MATLAB script as the optimization algorithm. Using the combination of these adaptive tools and methods, the preliminary results are considerably promising in terms of computation time, number of function evaluations, and the airfoil shape performance enhancement from both efficiency and pressure rise perspectives.

In the following sections, a literature review on optimization of airfoil geometry is presented. The optimization problem and the design approach are introduced. APRI is presented and explained. Last the optimization results, discussion and conclusion are included.

2. Shape Optimization of Heavy Duty Gas Turbine Airfoil

Optimization has recently become a key technology for product development in many industries. In turbomachinery design, usually there are many components or parts to be improved from aspects such as aerodynamics, structures, vibration, and so on. Thus optimization and specifically multidisciplinary optimization is essential for turbomachinery design. However, the optimization tends to require large computational power, especially when high fidelity analysis such as CFD or FEA is used in the design evaluation. Therefore, meta-modeling based optimization algorithms are of interest for such complex designs because they enable designers to conduct and perform the optimization process with less computation resources. Many approaches have been introduced and are being developed to handle these burdens by decreasing the computation efforts and/or increasing the quality of simulations for a compressor airfoils' shape optimization.

One of the newest works in this regard has been performed by Verstraete [4] in 2010, which has a good overview in his work on single/multi-objective problem formulations and optimization methods including zero order methods (random search and random walk, simulated annealing, Genetic Algorithm, Differential Evolution, Particle Swarm Optimization), first order methods (finite difference method, algorithmic differentiation, adjoint method) and second order methods. However, the work focuses on Differential Evolution (DE) and meta-model assisted DE.

Zheng *et al*. [5] in 2010 represented compressor blade geometry by integrating the B-Spline approach, a flow simulation/solver with a commercial CFD package-NUMECA, and GA. In addition, the response surface method was incorporated to approximate the objective function during the optimization process to save the time of simulation. The achieved result was evident improvement of both isentropic efficiency and pressure ratio at design and off-design conditions.

An appealing research in optimal design of compressor blade has been made by Sieverding *et al*. in 2004 [16]. The authors combined a parametric geometry definition method, a blade-to-blade flow solver and an optimization technique (breeder GA) with a proper fitness function. There are some novel aspects in this study, e.g. required flow turning and mechanical constraints are not considered as a part of the fitness function, and treated as killer criteria in GA. Also examination of the effect of weighting factors of the fitness function was carried out. The main purpose of this research work was to increase the compressor operating range compared to an earlier blade profile.

Sonoda *et al*. [7] in 2004 used evolutionary algorithms to develop high performance compressor airfoil at low Reynolds number conditions in order to improve the performance of the outlet guide vane used in a single low

pressure turbine of a small turbo fan engine for business jet aircraft. Sonda *et al.* adapted two different numerical optimization methods, the evolution strategy (ES) and the multi-objective genetic algorithm (MOGA) for the design process to minimize the total pressure loss and the deviation angle at the design point at low Reynolds number conditions.

Buche *et al*. [8] in 2003 presented an automated, multi-disciplinary optimization procedure for sub-sonic gas turbine compressor blades. They used evolutionary optimization algorithms coupled with existing tools for geometry generation, mechanical integrity analysis and Q3D flow analysis for design and off-design conditions. Their special focus was on a 3-D blade parameterization. The focus in this paper is on 2D blade geometry only.

Oyama *et al*. [9] in 2002 developed a reliable and efficient aerodynamic design optimization tool using evolutionary algorithm for transonic compressor blades. They used a real-coded adaptive-range GA to improve efficiency and robustness in design optimization. Three-dimensional Navier-Stokes computation is used for aerodynamic analysis and to represent flow fields accurately and produce reliable designs.

Kuster *et al*. [10] in 1999 presented a family of numerically optimized subsonic compressor airfoils for heavy-duty gas turbines, covering a wide range of flow properties. The objective of the optimization was to create profiles with a wide low loss incidence range. Design as well as off-design performance was considered in the objective function. They have also taken into account the special flow conditions in large-scale gas turbines by performing the numerical optimization procedure at high Reynolds numbers and high turbulence levels.

This brief literature review shows that different tools and approaches were used to carry on the optimization process of the airfoil shape or geometry to overcome aerodynamic forces and reduce pressure loss. None of these has used solely the metamodel based approach which is developed and used in this paper to achieve the same objective which is reducing the pressure loss through the optimization of the airfoil shape or geometry.

3. Problem Definition and Design Approach

The design problem is to optimize a typical compressor airfoil shape for efficiency increase in design and off-design performance. Integration has been first implemented among a CFD module of COMSOL Multiphysics as the flow solver, a curve fitting code developed in MATLAB environment, and finally the proposed global search algorithm, APRI, written in MATLAB.

After measuring the in-hand blade point cloud, the geometry parameterization is implemented using Non-Uniform Rational B-Spline (NURBS) curve [1] with MATLAB script. Actually the first step of all airfoil aerodynamic design approaches is having a proper parameterized geometry. For this purpose, there are several mathematical techniques including Bezier and NURBS as two popular ones. Considering all pros and cons of NURBS at the same time, its application in such geometry representation for optimizing purposes seems to be appropriate [11]. In this implementation, accuracy and robustness of the optimization process become the core issues. In this way, the NURBS control points' coordinates are considered as the design parameters in the optimization loop. To parametrically represent the airfoil geometry, however, a direct handling of airfoil shape which is creating distinct curves for the suction side, pressure side, leading edge, and trailing edge segments is employed in this study.

Besides the parameterization, formulation of the objective function has also a key effect on the results of the airfoil optimization process. When the parameterized profiles are made, they are fed to the COMSOL CFD for a 2-D fluid flow analysis. Following the convergence check, post-processed results of the accepted profiles are then entered to the fitness calculation part where the airfoils' loss values, L, related to any geometry are determined as follows:

$$\text{minimize} \quad L = a_1.L_s + a_2.L_d + a_3.L_c + P \tag{1}$$

Where a_i are the weighting factors, L_s, L_d, and L_c are total pressure losses for stall, design and choke conditions respectively, and P is the penalty function for geometry constraints. In addition to the profile limitations that have been considered in the geometric modeling, the minimum acceptable thickness of airfoils from structural issues point of view is taken into account. In terms of widening the range of operation, the minimization of total pressure loss at the right side and left side of the design point should be considered as formulated in Eq.(1) above. The weighting factors for the optimization process are specified as follows: $a1$=0.20, $a2$=0.70 and $a3$=0.10.

However, an important challenge in aerodynamic shape optimization problems is reduction of the computational effort as much as possible. This affects the designer's decision about the number and the type of shape parameters, geometric modeling methods, optimization algorithms, flow analysis tools, etc. In terms of optimization approach, for example, since the CFD analysis demands for massive computational effort, applying surrogate assisted algorithms seems to be a useful alternative. To achieve this purpose, a surrogate assisted optimization strategy named Approximated Promising Region Identifier (APRI), which is a modified version of SEUMRE [2], is introduced and used in this research. APRI works by exploring the whole design space by sending

agents (sampling points) to explore the design space. Based on the information obtained from all agents, the algorithm focuses the search in the most promising region by deploying more agents (generating more sample points) within the region. Latin Hypercube Design (LHD) [3], which is a well-known sampling technique, is used as a sampling technique to generate sample points. Once a promising region is identified, this region is refined by more sample points. A surrogate model or meta-model is then constructed to mimic the expensive objective function and help in searching for optimum solutions. In the following part, the paper describes in detail the APRI procedure.

4. Steps of the Proposed Optimization Algorithm

1) Generate a set of design data points over the design space;

$$x_i = \{x_1 . x_2, \ldots, x_n\}, \quad x_i \in S^p \tag{2}$$

where p represents the number of design variables and n is the number of initial design data point.

2) Evaluate the values of the objective function and constraints using the selected design points;

$$y \triangleq \min\{f(x_i) : (x_i, f(x_i)) \in S\} \tag{3}$$

where y represents the minimum of expensive function value.

3) Identify the new upper and lower boundaries of the promising unimodal region based on the obtained objective function values, using the same approach as in Ref. [2], points that are seized between these boundaries are considered neighboring design points, specifically
4) Once the new boundaries of the approximated promising region have been identified, refine the data set of this most promising region by adding more experiment or "expensive" points (points evaluated using the objective function) into the region (approximately 30-40% of the preliminary sample points) using Latin Hypercube Designs (LHD), and then introduce Response Surface Function (RSF) approximation model over the region;
5) Add more "cheap" design points that can be obtained using the easy-to-calculate approximation model (RSF). In the present approach, around 10000 (optional and depends on the complexity of the problem in hand) cheap points are generated using the meta-model over the promising unimodal region to identify the optimum point. A local optimizer can be used instead of generating these cheap points on the metamodel (optional);
6) Carry out the optimization search and identify the optimum point

Figure 1 shows the optimization algorithm APRI flowchart.

5. Results and Discussion

Table 1 shows the results obtained from APRI, which are considered promising compared to GA. GA has been used in the optimization of airfoil geometry for a long time. APRI outperforms GA and proves to be an efficient and robust algorithm. The results of APRI are shown at different termination criteria ε, which represents the difference between the actual and predicted function values. When ε is small it becomes harder for the algorithm to coverage to a global solution in less computation time but the accuracy of the results will be higher. It can be seen in Table 1 that with low ε values, APRI still yields results with high accuracy, which reflects the high performance of APRI. Using APRI, better airfoil geometries were found in less computation time. APRI with small ε =0.0001 converges to the optimum function value equal to 5.5063, which represents the minimum pressure loss. The function value 5.5063 is the best of the best among all function values. The other important factor that should be noticed is the number of function evaluations, which reflects how many evaluations is required to converge to optimum airfoil geometry presented in Table 2. Also CPU time (computation time) is an important factor that real world application pays much attention to. As can be seen in Table 1 that it took GA 117 hours to converge to minimum power loss equal to 5.9118 while it took APRI just 3.76 hours (13551 seconds) to converge to a more accurate and lower pressure loss value. It is clear that meta-modeling optimization algorithms are promising search tools for real-world applications such as the optimization of airfoil geometry for heavy duty gas turbines.

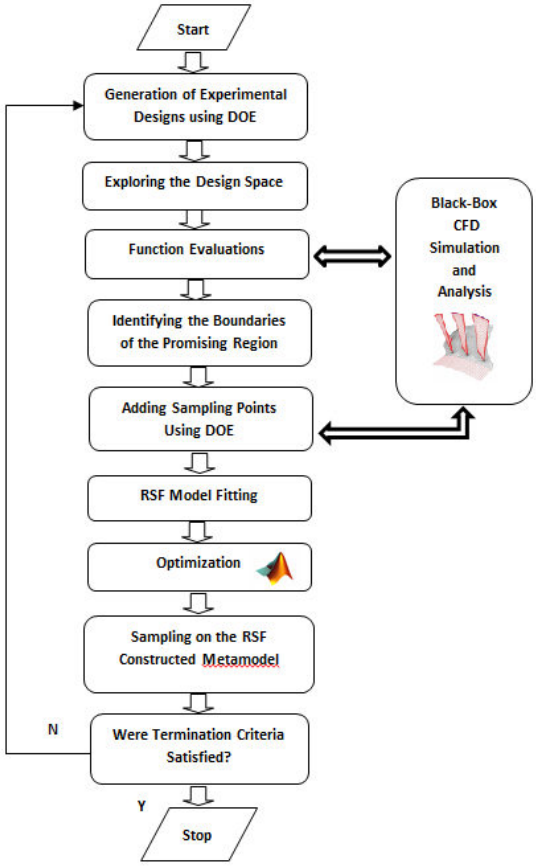

Figure 1: Approximated promising region identifier (APRI) flowchart

Table 1: Performance comparison and optimization results

Optimization Algorithm	Fun. Value	# Fun Eval.	# Iterations	CPU time (Sec)	Tolerance ε
APRI	5.9008	100	30	13551	0.01
	5.6189	160	50	34800	0.001
	5.5063	538	176	80300	0.0001
GA	5.9118	4080	50 (#generations)	421200	---

The simulation process was done more than one time because of the random nature of the meta-modeling algorithms and the way they search for optimum solution. Table 2 presents the results of five simulation runs.

Table 3 presents the average, median and standard deviation of the objective function value, number of function evaluations, number of iteration and average CPU time.

Table 2: Optimization results for five simulations

APRI	Fun. Value	# Fun Eval.	# Iterations
Run#1	5.9008	100	31
Run#2	5.6189	160	50
Run#3	5.5399	187	60
Run#4	5.4434	499	164
Run#5	5.7501	52	15

Table 3: Summary of APRI optimization results

Optimization Algorithm	Fun. Value		# Fun Eval.		# Iterations		CPU time (Sec)
	Median	STD	Median	STD	Median	STD	Average
APRI	5.6189	0.1794	160	175.41	50	58.5278	34800

Table 4 shows the parameters selected and used in GA algorithm. It is very important to select these optimization parameters for GA. The reason is that these parameters make a huge difference in the obtained optimum or the best obtained airfoil geometry. Changing one parameter might easily affect the results.

Table 4: GA parameters

Number of generations	50
Population size	80
Selection method	Stochastic Uniform
Crossover rate	0.95
Mutation probability	0.15

Figure 2 shows a schematic of profiles generated during the optimization runs. These profiles represent the best profile for each run. One of these profiles geneated represents the best airofoil profile which is the best or the optimum airofil genemoety.

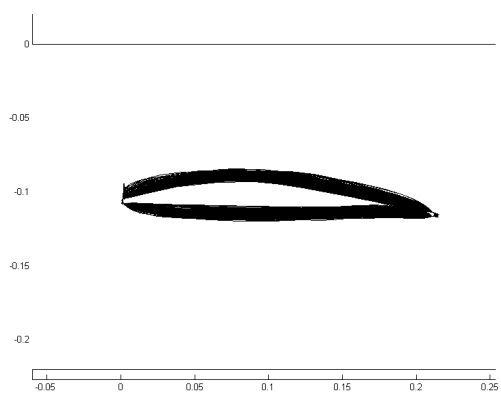

Figure 2: A schematic of profiles generated for the optimization loop

Figure 3 shows a comparison of airfoil geometry. The dotted line represents the un-optimized or starting (datum) airfoil geometry. The dashed line represents the airfoil geometry obtained using GA, and the solid line shows the optimized airfoil geometry generated using APRI.

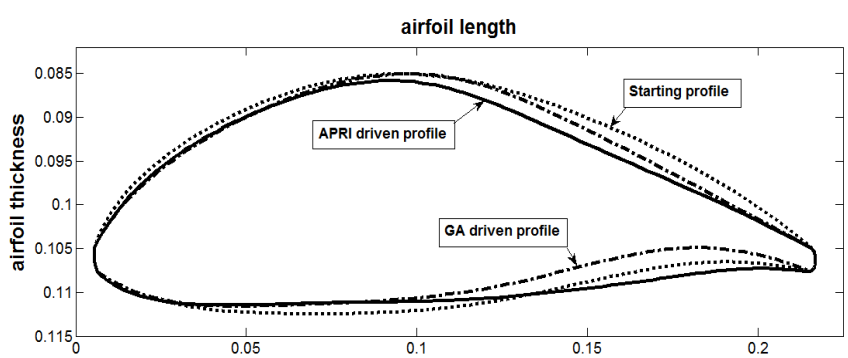

Figure 3: Airfoil geometry comparison

Figure 4 shows the pressure distribution comparison of APRI, GA and the Un-optimized case.

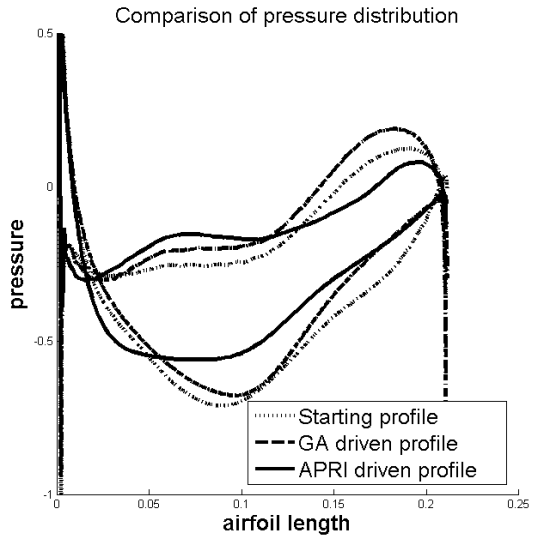

Figure 4: Pressure distribution comparison

The total pressure loss coefficient resulting from analysis of the initial airfoil as well as the optimum from incidence angle of -10 to +10 degrees have been shown in Figure 5. As illustrated in this figure, the APRI-driven profile outperforms the current shape in both design and off-design performance (i.e. about 1% reduction in total pressure loss at design condition (0° incidence angle) as well as increased operating range specifically for stall condition). While the airfoil's operating range for the stall condition is almost unchanged for profiles driven from GA optimization, APRI noticeably shows better performance in this regard. Nevertheless, in terms of the goals to be achieved as previously stated in the fitness function definition part, the figure addresses that GA gives more improvement of the compressor airfoil off-design behavior in choke condition (positive angles) comparing to APRI optimization.

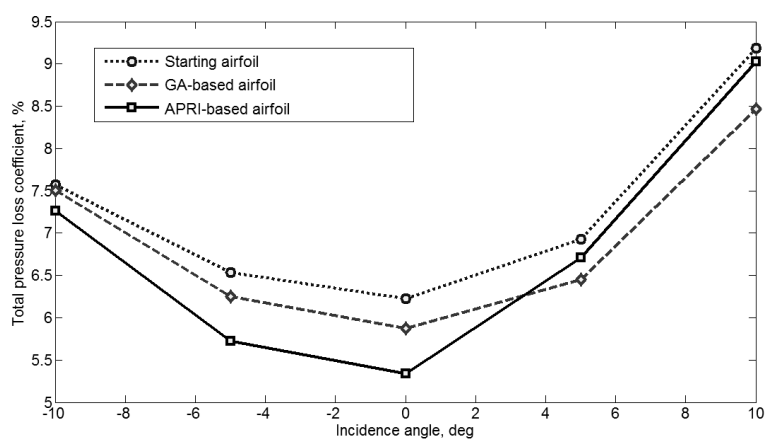

Figure 5: Airfoils operating range; datum design, GA optimized and APRI optimized shapes

6. Conclusion

With the objective of minimizing the total pressure losses for the design condition as well as maximizing the airfoils operating range, a design optimization carried out by integrating a computer code for the geometry

parameterization of the airfoils' shape, a blade-to-blade flow analysis in a commercial CFD tool, and a new meta-model-based optimization algorithm (APRI) developed for this case study. Using the combination of these adaptive tools and methods, the optimization achieved promising results as compared to generative algorithms. The developed APRI method has potential to be used for shape optimization in other applications.

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