# A MULTI-STAGE COMPRESSOR DESIGN OPTIMIZATION USING CFD

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## INTRODUCTION

A multi-stage compressor design is a typical multiobjective problem (MOP) involving some competing objectives such as maximization of efficiency, maximization of total pressure ratio, maximization of mass flow rate, minimization of weight, maximization of durability, etc. While single objective optimization problems may have a unique optimal solution, MOPs present a set of compromised solutions, largely known as the *Pareto-optimal* solutions. These solutions are optimal in the sense that no other solutions in the search space are superior to them when all objectives are considered (Fig. 1). Because the goal of MOPs is to find as many Pareto-optimal solutions as possible to reveal tradeoff information among different objectives, there is a demand for a systematic multiobjective design optimization method for compressor design optimizations.

The objective of the present study is to compare two popular design optimization methods, *i.e.*, the gradient-based methods and the evolutionary algorithms by applying them to a multi-stage axial compressor design optimization.

## DESIGN OPTIMIZATION PROBLEM

In the present study, a design optimization of a four-stage compressor with one guide vane, four rotors and four stators is demonstrated (Fig.2.). The objectives are maximization of both the overall isentropic efficiency and the total pressure ratio. The radial distributions of total pressure and solidities at rotor trailing edges and flow angles and solidities at stator trailing edges are chosen as design variables to be optimized because they have a direct impact on the overall efficiency as well as the total pressure ratio. These radial distributions are expressed by using a cubic-spline interpolation scheme where each curve is defined by five control points at specified radial stations. These control points are taken as design parameters. As a result, the design problem has 80 design parameters. The search range of each parameter is set to ± 10% of the baseline design. A constraint is applied to diffusion factor of each rotor and stator to be smaller than 0.55 to avoid obtaining designs with flow separations.

## AERODYNAMIC ANALYSIS

The computer program UD0300M is used for compressor performance evaluations. UD0300M solves the momentum and continuity equations assuming the flow through the compressor is axisymmetric and inviscid. The system of equations is solved by using the streamline curvature method. In the streamline curvature method, a computing mesh is formed by the intersection of the defined computing stations with the computed streamlines as shown in the Fig. 2. Using the resulting flow distribution, blade camber, blade chord and number of blades are obtained by running the blade geometry definition section of the program. Complete details of the formulation and the solution procedure are given in [1].

## GRADIENT-BASED METHODS

The gradient-based methods are one of the traditional design optimization methods developed to solve single objective optimization problems. In this study, the standard gradient-based method known as CONMIN [2] is adopted. CONMIN bases on the method of feasible directions and the gradient information of the objective and constraint function are calculated by finite difference. To

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apply the gradient-based method to the multiobjective compressor design optimization problem, the problem is transformed into a single objective optimization problem by combining the objectives into a single objective using the weighted sum method as:

$$F = w_1 \cdot f_1 + w_2 \cdot f_2 \ , \quad w_1 + w_2 = 1 \qquad (1)$$

## EVOLUTIONARY ALGORITHMS

The evolutionary algorithms [3] are a relatively new design optimization method, which mimics natural evolution by selection and reproduction. The evolutionary algorithms can uniformly sample various Pareto-optimal solutions in one optimization without converting a MOP into a single objective problem by maintaining a population of design candidates and using a fitness assignment method based on the Pareto-optimality concept.

The present evolutionary algorithm uses Fonseca's Pareto-based ranking method for fitness assignment to introduce the Pareto-optimality concept (Fig. 3). The best *N* selection is used to select individuals according to their ranks where a standard sharing function is incorporated to maintain diversity in the population. The present method adopts the real coding, the blended crossover, and the uniform mutation. Population size and number of generations are set to 300 and 1000, respectively. For more detail of the present evolutionary algorithm, see [4].

## RESULTS

Figure 4 presents the overall isentropic efficiency and the total pressure ratio of the baseline design and the Pareto-optimal designs obtained by the gradient-based method and the evolutionary algorithm. The present evolutionary algorithm (indicated as MOEA(p300g1000), which means the population size 300 and the generation 1000) found reasonable Pareto-optimal designs including a design that improved the isentropic efficiency by over 1% (from 0.866 to 0.876) while maintaining the total pressure ratio and a design that improved the total pressure ratio by more than 9% (from 5.19 to 5.66) while maintaining the efficiency.

While the gradient-based method found a few non dominated solutions, it generally produced solutions dominated by MOEA results. This implies that the objective function distribution of the compressor design is multi-modal, although the Pareto front is convex.

Finally, because the gradient-based method can find some of non dominated solutions efficiently, the solutions obtained from the gradient-based method were seeded into the initial population for the present evolutionary algorithm. The corresponding results are indicated as GBM+MOEA(p200g300). The resulting non dominated solutions cover a wider front, especially for extreme regions even with a smaller number of the population size. This type of hybridization for MOEA seems very promising.

## CONCLUSIONS

A multiobjective four-stage compressor design was demonstrated to compare the gradient-based methods and the evolutionary algorithms. While the evolutionary algorithm obtained numbers of reasonable and uniformly distributed Pareto-optimal designs, the gradient-based method failed to show the tradeoff information between the two objectives. The present paper showed the evolutionary algorithms are suitable for compressor design optimizations.

## REFERENCES


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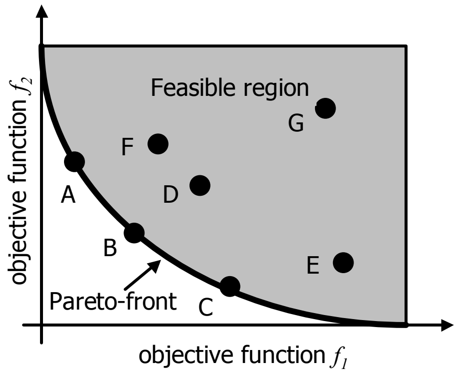


**Figure 1.** The concept of Pareto-optimality. This is an example of MOPs, which minimizes two conflicting objectives $f_1$ and $f_2$. This MOP has innumerable compromised Pareto-optimal solutions such as solutions A, B, and C. These solutions are optimal in the sense that there is no better solution in both objectives. One cannot say which is better among these Pareto-optimal solutions because improvement in one objective degrades another.

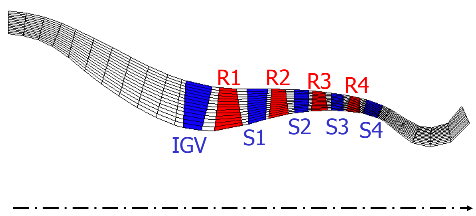


**Figure 2.** The baseline design.

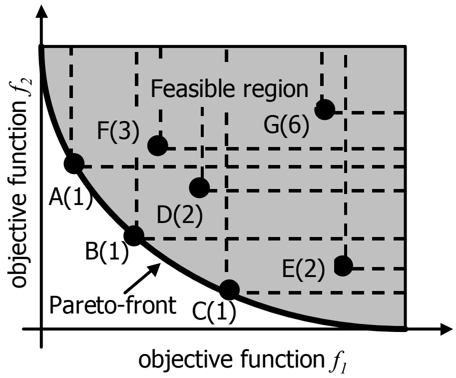


**Figure 3.** Fonseca's Pareto-ranking method for a multiobjective minimization problem. Because the solutions A, B, C are Pareto-optimal these solutions rank first. The solutions D and E rank second because they are worse than the solutions B and C on both objectives, respectively. The solution F ranks third because two solutions (A and B) are better than the solution F on both objectives.

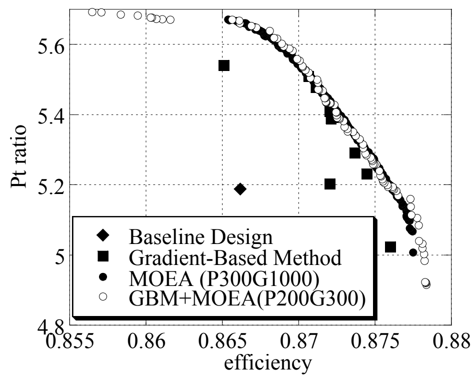


**Figure 4.** Pareto-optimal designs.