Efficient Global Optimization for S-duct Diffuser Shape Design

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Abstract: The efficient global optimization (EGO) method is a global optimization technique based on the stochastic kriging model to efficiently search the global optimum in a design space. EGO selects the next sample point in the view of the probability that a global minimum is located. To present the probability the EGO method introduces the expected improvement (EI) function. The mean and variance at the untried point provided from the kriging model are used to calculate the EI function. EGO selects the maximum EI point as the next sample point. After validating the EGO method by several test functions, we applied it to a diffusing S-duct shape design problem which needs a computationally expensive turbulent computational fluid dynamics (CFD) analysis. The design objective is to improve the total pressure recovery of the S-duct. The improved S-duct shape was searched globally through the EGO method. Our results confirmed that the EGO method efficiently provided a meaningful engineering result in the S-duct shape design.

1 Introduction

The diffusing S-duct is a typical aircraft inlet geometry. It decelerates air entering the compressor and increases the static pressure. The Lockheed Matin F-16 has a chin-type S-duct and Korean advanced supersonic trainer T-50 has a bifurcated S-duct.

A well designed diffusing S-duct can help to enhance engine performance by delivering a nearly uniform flow with a small transverse velocity component at the engine compressor entrance. But the centerline curvature associated with the S-duct makes a centrifugal force and cross-stream pressure gradient between the bottom and the top of S-duct. As a result the diffusing S-duct integrates the complex 3-dimensional internal flow which includes secondary flows and flow separation. Wellborn et al. [1] performed a compressible subsonic flow experiment through a representative S-duct configuration and investigated the complicated flow mechanism in detail. The baseline diffuser of our design corresponds to the experimental configuration of Wellborn et al.

The aerodynamic performance of subsonic diffusers is principally determined by two parameters; the flow distortion at the outlet of the diffuser and the total pressure recovery. If the flow distortion is reduced and the total pressure recovery is close to one, it can be considered to be well-designed.

To estimate performance characteristics of an S-duct without experiments, computational studies have been done with different turbulent models. Harloff et al. used the PARC3D computer program to solve the full, three-dimensional Reynolds-averaged Navier-Stokes equations. Harloff et al. computed a subsonic S-duct flow using the Baldwin-Lomax algebraic turbulence model and the k-ε turbulent model. Zhang et al. performed computational analysis of the S-duct diffuser by utilizing the Baldwin-Lomax turbulent algebraic model. Details are presented by Zhang. Lee and Kim analyzed the S-duct computationally and concluded that k-ω shear stress transport (SST) the two equation turbulent model predicts the flow characteristics better than Spalart-Allmaras and k-ω.

For the optimization method of S-duct shape, the sequential quadratic programming (SQP) and the adjoint equations were used. Both are gradient-based optimizers. The multi-objective genetic algorithm (MOGA) was also used as a global search method.

Generally gradient-based optimization methods provide an accurate local minimum in the design space, but such optimization requires sensitivity information to calculate the search direction. Using the adjoint equations, the sensitivity can be computed at once irrespective of the number of design variables. However, applying the adjoint equation to a specific analysis code is still limited for engineers to use in the field. The genetic algorithm also has the demerit of needing a lot of evaluating function.

Thus, surrogate-based optimization has become a noteworthy method nowadays. With a surrogate model, the global minimum can be searched for by looking at and investigating the design space, and a surrogate model can be constructed with a few analysis runs. Another advantage is that previously analyzed data can be reused to build a surrogate model later after it has been stored. However, the difficulty of surrogate-based optimization is in selecting the next sample point that can cover the local and global search in the design space.

For this reason, Jones et al. [2] developed the efficient global optimization (EGO) method based on the stochastic kriging model. EGO selects the next sample point that has the maximum probability that the global minimum exists. The probability is expressed by the expected improvement (EI) function, which consists of the mean value and the variance of the kriging model. The uncertainty(=variance) of the kriging model at untried points is considered not a risk but an opportunity to search for a good solution. Because the EGO method needs a minimal number of analysis runs to search a global minimum, the EGO method can be a good way for optimization when the analysis is computationally expensive such as in a CFD analysis.

The objective of this research is to apply the EGO method to the diffusing S-duct shape design and to investigate the usefulness of the EGO method.

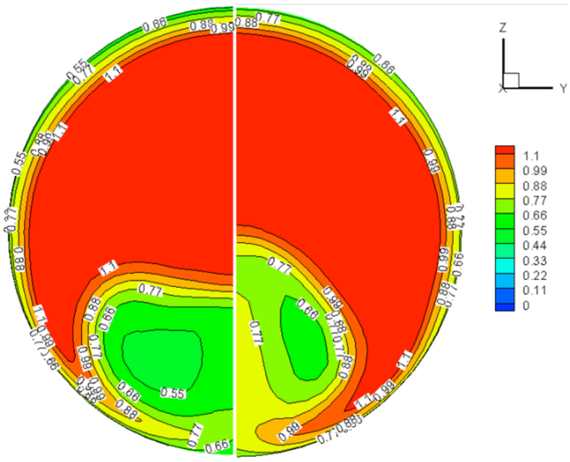

Fig. Original (L) and designed (R) S-duct outlet : total pressure coefficient

References

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[2] Jones D. R., Schonlau, M. and Welch, W. Efficient global optimization of expensive black-box functions, Journal of Global Optimization, 1998, 13, pp. 455-492