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Optimal design of aeroengine turbine disc based on kriging surrogate models

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ABSTRACT

A design optimization method based on kriging surrogate models is proposed and applied to the shape optimization of an aeroengine turbine disc. The kriging surrogate model is built to provide rapid approximations of time-consuming computations. For improving the accuracy of surrogate models without significantly increasing computational cost, a rigorous sample selection is employed to reduce additional design samples based on design of experiments over a sequential trust region. The minimum-mass shape design of turbine discs under thermal and mechanical loads has demonstrated the effectiveness and efficiency of the presented optimization approach.

1. Introduction

In advanced propulsive systems, a turbine disc bears vast mechanical and thermal loads under its working conditions of high temperature gradients and high rotational velocity, which may induce intensive stresses and dangerous damages. A significant objective of the shape optimization of the turbine disc is to minimize its mass subject to constraints on the stresses and some other practical conditions. Clearly, an effective optimization method will be valuable to enhance the quality of the turbine disc and hence to improve the engine specific thrust, thrust-to-weight ratio, and system reliability.

With the growth in computing power of current computers, computationally expensive finite element (FE) method has become a common and important technique in the product development process, and a large number of FE codes, including commercial packages and in-house codes developed have been mainly used for function evaluations (evaluations of the objective and/or constraint functions), such as stress analysis, thermal analysis, vibration analysis and fatigue life estimates in the design and optimization of aeroengine discs [1–4]. However, the optimization design of a complex system like a gas turbine often involves exploring a broad design space. This requires analyzing large numbers of design points. If all evaluations of these designs are performed using computationally expensive FE method, it will lead to an excessive computational cost and therefore an impractical runtime of the optimization process.

One alternative is to construct a simple surrogate model to approximate the response of the costly FE solvers. The surrogate model expresses the relationship between the objective or constraint functions and the design variables with simple form equations. The surrogate model can be used to cover regions in the design space for which a solution cannot practically be obtained. In addition, the use of surrogate model often requires only a small number of expensive FE analyses and can reduce significantly the computing time in obtaining the optimal design. Therefore, the approximation approach has been widely applied to engineering optimization problems so as to reduce the computational cost.

There are several different categories surrogate models (also called meta-models or approximate models) for engineering design problems [5,6], including the polynomial-based response surface model [7,8], the neural networks (NNs) based surrogate model [9,10] and the kriging model [11–13].

A polynomial-based response surface model is a most widely used surrogate model due to its simplicity and effectiveness. The response surface method uses least-squares regression analysis to fit low-order polynomials to a set of experimental data. Because the polynomial-based response surface model normally requires the assumption of the order of the approximated base function, the designer must evaluate the schematic shape of the objective function over an entire solution space. This will sometimes be difficult since it requires an understanding of the qualitative tendency of the entire design space. Besides, the model function is typically chosen to be first- or second-order polynomials, because a higher-order polynomial not only tends to show severe oscillations but also

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requires too many support points [14]. This may result in limited accuracy of the response surface model when the response data to be modeled have multiple local extrema. Therefore, the polynomial-based response surface model is likely awkward when it is used for representing multi-modalities and non-linearity commonly appeared in complex engineering problem [15].

Neural networks are inherently massive parallel computational systems comprised of simple nonlinear processing elements with adjustable interconnections. The predictive ability of the network is stored in inter-unit connection strengths called weights obtained by a process of adaptation and learning from a set of design training data. Training of a network requires repeated cycling through the data and continues until the error target is met or until the maximum number of neurons is reached. So, neural networks are quite powerful and flexible when it comes to handling complex interacting functions, irregular, non-smooth, discontinuous or nonlinear design spaces. Due to the feature of neural networks, the NNs-based surrogate model has good performance in prediction accuracy for complex engineering problems. However, NNs-based model presents some practical difficulties. For example, this mode requires a good many sample points and much computation time for the training of NNs [16].

Recently, kriging models have drawn much attention and been widely used in a variety of applications such as structural optimization [17,18], multidisciplinary design optimization [19,20] and aerospace engineering [11,21]. This type of models predicts the value of the unknown point using stochastic processes. Sample points are interpolated with the Gaussian random function to estimate the trend of the stochastic processes. The model has a sufficient flexibility to model response data with multiple local extrema and to represent the nonlinear and multimodal functions, though this flexibility is obtained at an increase in computational expense and a decrease in ease of use [17,22].

One important issues associated with adaptive optimization strategies based on the knowledge obtained from the surrogate model is the sequential updating of an approximate model with additional data, which is also called sequential sampling. Various methods for sequential sampling in the design space have been studied in recent years. Space-filling designs and the expected improvement concept were introduced by Jones et al. [23] as an efficient sequential sampling strategy in the efficient global optimization (EGO) algorithm, where the expected improvement criterion is used for the balance between local and global search. For the infill sample selection in the global optimization of stochastic black-box systems, Huang et al. [24] adopted an augmented expected improvement function with desirable properties for stochastic responses. Besides, Lee and Kang [18] used other two sequential sampling strategies simultaneously for improving the accuracy of kriging model. One was to select a new sample point by maximizing the mean square error of the initial kriging model, and the other was to select the new sample point as a stationary point. What's more, Farhang-Mehr and Azarm [25] introduced a sequential maximum entropy design approach so that the response function behavior could be automatically adapted by emphasizing the irregular regions of the design space and designing the next set of experiments accordingly. In addition, Xiong et al. [26] introduced a sequential sampling procedure that use design confidence as a metric to assist designers in making decision regarding when to terminate the sampling process so that the current optimal design can be accepted as the "true" optimal solution with desired confidence.

The other important issue associated is the framework for the management of surrogate models. Frameworks based on trust regions and gradient-based search procedures have attracted much attention in the past few decades [27–29]. These rigorous frameworks guarantee convergence to a model local optimum and work with nonlinear programming techniques or direct-search methods. Besides, several attempts have been made to tackle the problem of using surrogate models with evolutionary search methods. Ratle [30] proposed a simple local convergence criterion to decide when the exact model should be resorted to in a procedure integrating a genetic algorithm with kriging models. However, this does not prevent the search from converging to false optima. Jin et al. [31] proposed a framework for coupling evolutionary strategy and NNs-based surrogate models. Two types of evolution control methods were presented to decide the frequency at which the exact model should be used. Song and Keane [32] coupled a real-coded genetic algorithm with a kriging surrogate model in order to reduce computational cost without sacrificing the ability of the GA in finding the global optimum for complex landscapes, using a new approach based on the posterior variance estimate to suggest new sample points for re-evaluation using exact models. New sample points obtained were inserted into an ordered database storing all the exact solutions evaluated so far, and the surrogate model was updated when these new points felled into the section of the dataset used in the construction of the surrogate model.

In this work, we explore a method combining a robust archived differential evolution (RADE) algorithm [33] with kriging surrogate models so as to reduce the total number of expensive function evaluations and therefore the computation effort in the shape optimization of aeroengine turbine disc. The kriging model is constructed on the base of data collected by evaluating the objective and constraint functions at a few initial points, and afterward updated gradually with additional sample points. At each iteration the kriging model constructed is invoked repeatedly by the robust archived differential evolution algorithm to estimate the location of the optimum and suggest points where additional function evaluations may help improve this estimate. A new additional sample point will be analyzed and inserted into the design dataset for the update of the kriging model, until the kriging model is sufficiently accurate and the optimization process is converged.

2. Problem formulation

2.1. Optimization model

The turbine disc can be simplified as an axi-symmetric rotating disc with a centric bore. The circular cylindrical coordinates (r, θ, z) are adopted for the convenience of description and analysis in this paper, where the symmetric axis z and the axial direction of the turbine disc are consistent with each other. The half-axial cross section of the turbine disc is shown in Fig. 1, where the disc shape is defined with several geometric parameters, including the dead rim radius (R_1), bore radius (R_2), web outer radius (R_3), web inner radius (R_4), dead rim width (W_1), bore width (W_2), web outer width (W_3), web inner width (W_4), dead rim height (H_1) and bore height (H_2).

Among these geometric parameters above, the dead rim radius (R_1), bore radius (R_2), dead rim width (W_1) and dead rim height (H_1) can commonly be predetermined according to requirements on other components such as the turbine blade and the gas flow passage. The other six geometric parameters are identified as design variables and their ranges are given in Table 1.

Constraints for the turbine disc optimization consist of size constraints and performance constraints. The size constraints limit the variable ranges. The performance constraints, such as life-span, stress and structural transformation, are always set according to a design rule. In this paper, we consider the radial stress and circumferential stress in the disc as the performance constraints for minimizing the disc mass.