International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
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IJIEMR Transactions, online available on 27th Oct 2018. Link

:http://www.ijiemr.org/downloads.php?vol=Volume-07&issue=ISSUE-11

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Volume 07, Issue 11, Pages: 94-100.

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PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
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STRUCTURAL ENGINEERING SINGLE AND MULTIPOINT SHAPE OPTIMIZATION OF GAS TURBINE BLADE CASCADES

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Abstract

A multi-objective, reliability-based design optimization technique of acompressor blade is proposed using response surface methods and geneticalgorithms. The design objectives are to maximize the stage pressure ratio and to minimize the weight of the NASA rotor67 transonic blade, whilesatisfying both aerodynamic constraint and structural reliability constraint.Thirty two deterministic design variables are used to deny the shape ofthe blade, while two random variables are used to characterize the uncertainties in material properties. Reliability analysis is performed using thesecond-order response surface and Monte Carlo simulation. The probabilistic suciency factor, which is superior to the probability of failure andsafety factor in terms of accuracy in the regions of low probability of failure when calculated using Monte Carlo simulation, is used as an alternativemeasure of safety in reliability-based design optimization. Quadratic designresponse surfaces are utilized to later the noise from the Monte Carlo simulation and also facilitate the multidisciplinary design optimization. Thegenetic algorithm is employed to

¯ nd the Pareto-optimal solutions. To expedite the convergence and ¯ nd a well-converged solution, we also use a local search.

Introduction

For decades, many researchers have used optimization techniques to improve the engineperformance. Some focus on a speci¯ c discipline, others involve in multi-disciplines. Forinstance, Oyama et al.1 minimized the entropy generation of the NASA rotor67 blade,Benini2 improved the total pressure ratio and the adiabatic e±ciency of the NASA rotor37blade, Mengistu and Ghaly3 performed multi-point design of compressor rotors to improvetheir aerodynamic performance, Lian and Liou4, 5 performed multidisciplinary and multi-objective optimization of the NASA rotor67 blade with a coupled genetic algorithm andresponse surface technique. In the aforementioned works, the design variables were assumedknown deterministic parameters. For engine design, however, uncertainties and randomness exist in the material properties and design variables. To ensure robust and reliable designs,we need to account for these uncertainties or randomness in the optimization procedure.

Reliability-based design optimization (RBDO) is a technique to consider the

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uncertaintyof input parameters in the design process. It provides not only the performance valuebut also the confidence range. On the other hand, RBDO involving a computationallydemanding model has been limited by the relatively high number of required analyses foruncertainty propagation during the design process. In order to overcome this limitation,several alternatives with various degrees of complexity, such as moment- based methods11, 12and Monte Carlo simulation (MCS), have been proposed. The moment based-methods

arerelatively e±cient because they approximate the performance measure at the most probablepoint using linear of quadratic functions. However, the accuracy of these approximations isa concern when the performance function exhibits nonlinear behavior. Another drawback ofmoment-based methods is that they are not well

suited for problems with many competingcritical failure modes.13 The MCS is a simple form of the basic simulation. It provides apowerful tool for evaluating the risk of complex engineering systems. It is widely used inreliability analysis because of its simplicity and robustness. Nonetheless, the MCS requires alarge amount of analyses for a good estimation of the probability of failure, especially whenthe failure probability is small. And MCS can also produce noisy response.13 Responsesurface approximation has the capability to handle these two problems. In addition, the

use of response surface approach facilitates multidisciplinary optimizations, which face thechallenges of computational expense and organizational complexity.

In this paper, a multi-objective RBDO of a NASA rotor67 compressor blade is proposedusing response surface techniques and genetic algorithms. The objectives are to maximize the stagepressure ratio and to minimize the blade weight while satisfying the constraints onreliability of maximum blade stress and mass °ow rate. A real-coded genetic algorithm isused to facilitate the multi-objective optimization. The limits on reliability constraints areset up such that the probability of failure is less than 10¡4. Thirty two deterministic designvariables are used to determine the shape of the blade, while two random variables are usedto characterize the uncertainties in material properties. In order to address the aerodynamicperformance as well as the structural performance, a sequential analysis technique has beenadopted in which structural deformation does not in°uence on aerodynamic performance.

This assumption is valid when the structural deformation is small. The response surface isbuilt based on the preselected design points. Their aerodynamic and structural performancesare evaluated using high-

¯ delity tools. A computational °uid dynamics (CFD) tool is usedto compute the aerodynamic force, which is then transferred from the CFD grid to thestructural ¯ nite element grid. To ensure the conservation of energy between the °ow and thestructural systems, the thin interpolation is used as the interpolation technique.7, 23 A+commercial

¯nite element analysis program, ANSYS, is then used to compute the maximumvon

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Mises stress at the top and bottom surfaces of the blade. The RBDO is performed onthe response surface using the genetic algorithm and MCS.

Proposed method

The design uncertainty camefrom the material properties. Our objectives were to maximize the stage pressure ratio whileminimize the blade weight. A second-order response surface model was built to make itpossible to perform such a computationally intensive analysis and optimization process.

Results and discussion

In the problem described in Eq. (1) there are 32 design variables and two random variables. The objective functions and the aerodynamic constraint therein are only a®ected bythe designvariables while the maximum stress is a®ected by the design variables and Poisson's ratio. The random variable, endurance limit, which is factored into the computation ofprobability su±cient factor, does not in°uence the maximum stress. Therefore, our samplingof design points is based on the 32 design variables and random variable Poisson's ratio. Wesample 1,024 design points with the hypercube Latin sampling. These design

points are evaluated using the aforementioned °uid and structure solvers. Thereafter, the ARS is built forthe maximum von Mises stress based on both the design variables and the random variable.

The accuracy of the response surface approximation is evaluated by statistical measures,including the adjusted coincident of determination (R2adj) and the root mean square error(RMSE) predictor. The adjusted coincident of determination is more comparable over models with di®erent numbers of parameters by using the degrees of freedom in its computation.

It measures the proportion of the variation accounted for by ¯ tting means to each factorlevel. Table 2 shows the test results. The value of R2adj for the maximal stress is 0.8369;the stage pressure rise has a value of R2adj larger than 0.98 and a RMSE% close to zero,indicating the quadratic response

surface model gives accurate representations.Monte Carlo simulation is performed based on the built ARS. For a problem requiredfailure probability of 1:0£10¡4, one million simulations are performed at each design point.

After the probability of failure and probability su±cient factor are extracted, we are ready tobuild the DRS based on the design variables. The statistical measures are shown in Table 2.We can see that the ¯ tting of the failure probability is poor in terms of the statisticalmeasures. Fig. 4 shows the distribution of the failure probability, which changes severalorders of magnitude over a narrow range. A quadratic response surface may not be e±cientto capture the change. A high-order response surface model may be required to capture thesteep variation. However, it demands more design points to

¯t the coe±cients. In addition,we can see that more than 90% of the design has a zero failure probability. Not enoughgradient information will be provided in the optimization procedure if a response surfaceis built based on the failure probability. If safety factor is used, we still

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could not avoid the large portion of °at region. On the other hand, the design response surface for the probability su±cient factor has good statistical measures. The values of *R*2 adj and %RMSE are 0.9994 and 0.002337, respectively. We plot the distribution of *Psf*in Fig. 5, which shows a smooth variation. For the studied problem with 1 million simulations and a required probability of failure less than 10¡4, the error associated with the limited size of simulation is 2 £ 10¡5, which is much less than that the value of 0.002637 due to the design response

Error Statistics	p_{02}/p_{01}	W	$\dot{m}$	S_N	p_f	P_{sf}
R^2	0.9949	0.9999	0.9979	0.9262	0.6638	0.9994
R^2_{adj}	0.9888	0.9999	0.9954	0.8369	0.2572	0.9987
RMSE	0.564e-3	0.800e-5	0.4246e-2	0.1282E8	0.2851e-1	0.2637e-2
%RMSE	0.3000e-3	0.1175e-3	0.1270e-3	0.2761e-1	0.1425e3	0.2337e-2

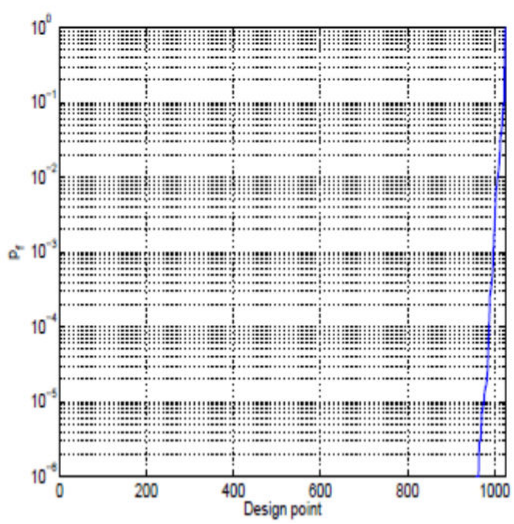

Figure 4. Distribution of probability of failure of the 1024 design points.

Our problem described in Eq. 1 is a multi-objective optimization problem with a set ofPareto-optimal solutions. To facilitate the optimization, we use a real-coded genetic algorithm. With the we set the population size as 320. Fig. 6 shows the solutions with differentgeneration sizes. The convergence rate at the beginning is fast and it gradually slows down.

This phenomenon is typical for genetic algorithms, which usually suffer a slow convergencerate when the optimal is approach. One remedy is to use a hybrid method. The basic ideais to switch to a gradient-based method to improve the convergence after the genetic algorithm. For that purpose we use the Design optimization tools (DOT),24 which is softwarebased on gradient-based methods. Fig. 6 shows that DOT does improve the convergence.

Optimization is also attempted exclusively based on gradient-based methods. To do that,we transform the original problem in Eq. (1) into a single objective optimization problemby introducing weight function and DOT is employed as the optimizer. We notice that eventhough it obtains some solutions better that those from the hybrid method, the gradient-based method fails to identify some regions on the Pareto-optimal front. In addition, wenotice that the gradient-based method is sensitive to the initial condition. The solution from

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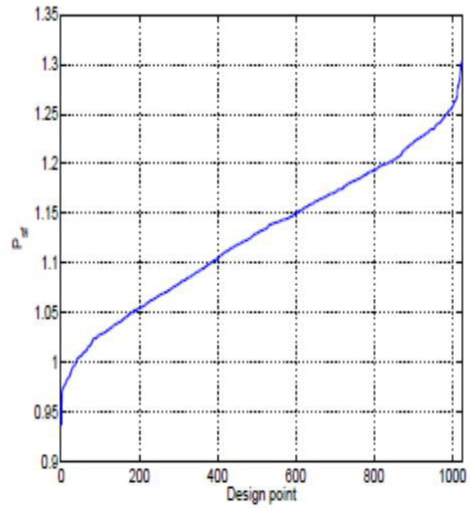

Figure 5. Distribution of probability suffcient failure of the 1024 design points.

genetic algorithms is also affected by the initial condition. However, the effect demolisheswiththe increase of generation size. We compare Pareto-optimal fronts with different initialconditions and ¯ nd no evident difference at the 8000-th generation.

Totally there are 693Pareto-optimal solutions lying on the front.

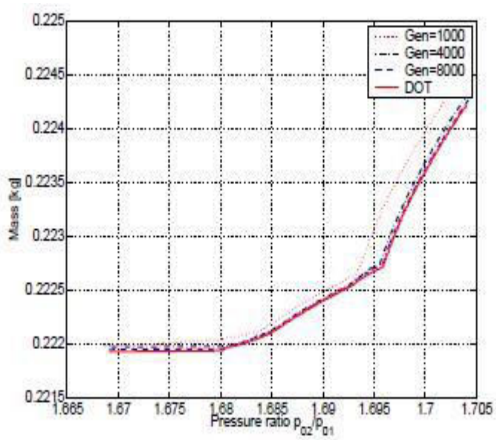

Figure 6. Genetic algorithm convergence history and solutions from hybrid method.

We choose 15 representative optimal design points from the Pareto-optimal front usingthe K-means clustering algorithm to verify against the high-¯ delity analysis tools. K-meansclustering is a method that chooses a set of data points from the Pareto-optimal front toaccurate represent the distribution of whole date points 4, 25 The distribution of the selecteddata points is shown in Fig. 7. We also compare the baseline with the optimal solutions.Clearly the optimization process decreases the blade weight while increasing the stage pressure ratio.

To see the impact of the accuracy of ARS, we validate the probability sufficient factor ofeach representative optimal design using MCS by substituting the optimal values into the constructed ARS. This calculated PSF is compared with that predicted from optimizationprocess. The comparison is illustrated in Fig. 8. These two set of data have a correlationcoefficient of 0.9913, indicating that quadratic response surface ¯ fitting of the probabilitysufficient factor is an accurate approximation.

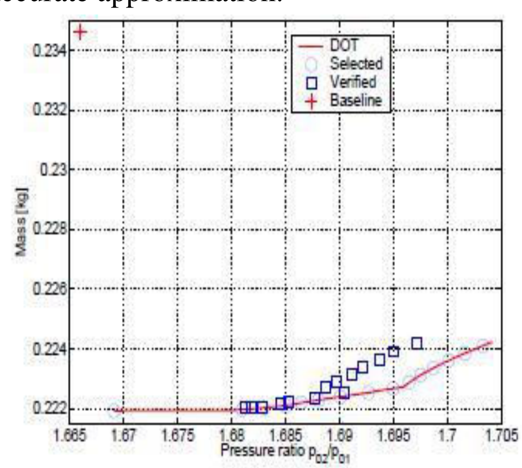

Figure 7. Comparison of baseline with optimal solutions.

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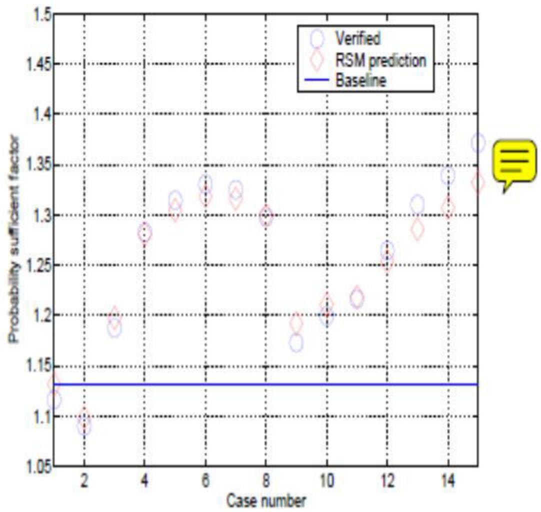

Figure 8. Correlation of probability su±cient factor from MCS and optimization.

Conclusions

In this paper, we demonstrated a reliability-based design optimization technique whenboth aerodynamic and structural performances are considered. The design uncertainty camefrom the material properties. Our objectives were to maximize the stage pressure ratio whileminimize the blade weight. A second-order response surface model was built to make itpossible to perform such a computationally intensive analysis and optimization process. Agenetic algorithm was used to facilitate the multi-objective characteristics of our problem. The reliability analysis was performed based on Monte Carlo simulation. Our numericalresults showed that we could achieve a new design with lighter weight, larger pressure ratio,and reliable performance.

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