IOSO Multilevel RDO Methodology

Here we present our methodology of solving RDO problems. This methodology is based on a combination of various fidelity analysis tools (for example 3D CFD simulation as a high-fidelity tool and adaptive surrogate model as a low-fidelity tool). Adaptive surrogate model tool is used for the evaluation of probability objectives during optimization which allows sufficiently speed-up the optimization problem solution and makes it possible to solve an RDO problem within the appropriate time limits [1].

Introduction

Designing a complex technical system in present-day conditions is difficult without the use of optimization techniques. In fact, design and optimization processes are intimately related. While designing a technical system and determining its parameters, an experienced designer is implicitly assessing the practical implementation of the system.

However, the rise of the complexity of systems as well as the number of parameters needed to be coordinated with each other in an optimal way have led some to consider the use of mathematical modeling combined with numerical optimization techniques. In this situation the designer focuses on developing an adequate mathematical model and on analyzing the results obtained. Choosing optimal parameters for the system being designed is done through the use of formal mathematical optimization procedures. The use of such an automated design approach exempts the designer of routine work required to select optimal combinations of variable parameters, allowing him to set and solve extremely complex problems with large numbers of variables. However, solutions obtained by means of mathematical modeling and optimization techniques in many cases are hard to implement in real life. This is largely due to the fact that while stating and solving optimization tasks by traditional (deterministic) approach, as a rule, various uncertainties influencing the efficiency of the designed system in real life conditions are not taken into consideration.

An extremum value of efficiency obtained from an optimization problem solved in a deterministic way may sometimes be a non-optimal design from a practical implementation point of view. In recent years, probabilistic design analysis and optimization methods have been developed to account for uncertainty and randomness through stochastic simulation and probabilistic analysis (see, for example, [2]-[13]). These methods can be classified as a new scientific direction named "Robust Design Optimization" (RDO). The distinct feature of this direction is the use of probabilistic objectives to evaluate the technical system quality. Despite a great variety of problem statements and the methods to solve optimization problems in conditions of uncertainty, there are a number of common problems that should be addressed by the investigators. These problems are as follows:

- *Identifying the main uncertainties affecting the design (i.e. uncertainties in variables in real operating environment; uncertainties in environmental conditions; uncertainty in mathematical model accuracy).*
- *Selecting the probabilistic objectives (for example: mean value of efficiency; magnitude of efficiency value deviation; probability that efficiency value is no worse than the one given; efficiency value ensured with probability no less than the one given).*
- *Selecting of procedure for probability objectives evaluation (analytical approach; Monte-Carlo technique and so on).*
- *Selecting the optimization method.*

The challenge of RDO problem

Let’s start the considering of RDO problem from questions “why do we need RDO?” and “what is RDO?” The problem of Robustness appears when any random variable considerably influences on the efficiency indexes of your object. For example on the Fig. 1 we show how radically some small change in the geometry parameter of a compressor blade may influence on the efficiency of real-life compressor. This influence has obviously random nature.

Fig. 1 Stochastic distribution of compressor efficiency indexes due to geometry variations

That means while solving an optimization task we don’t know the exact values of efficiency indexes, so the efficiency values are random ones. To handle optimization problems having random peculiarities of efficiency index values we have to involve probabilistic assessments of these efficiency indexes that is we need to use probabilistic optimization objectives. As probabilistic objectives we may use:

- mean value of efficiency;
- magnitude of efficiency value deviation;
- probability that efficiency value is no worse than the one given;
- efficiency value ensured with probability no less than the one given, and so on.

Fig. 2 shows some important example of the critical difference between optimization approaches in deterministic and RDO ways.

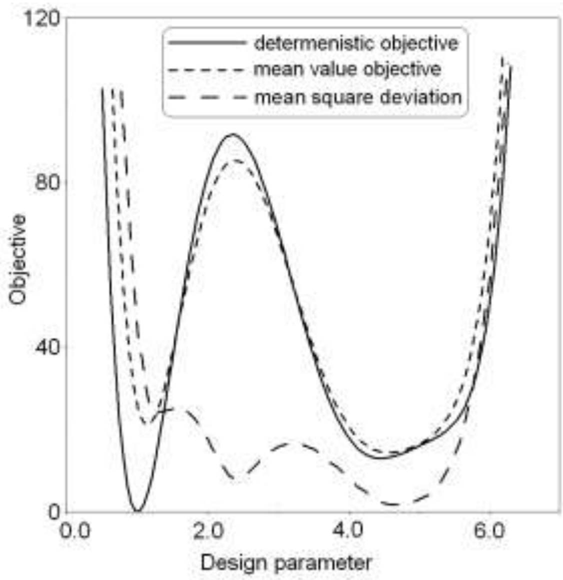

Fig. 2 Examples of probability objectives.

It is obvious that in this case the minimum of given deterministic solution is reached at $x = 1$. But if we take into consideration the random uncertainties in design parameter x values and consider the objective with the involvement of probabilistic approach, we can see that the minimum of the objective mean value would be at $\bar{x} \approx 4.6$ and it would be different from the deterministic minimum. It would be the same if the probabilistic objective is mean square deviation as well. **The considered example leads to an important conclusion that an RDO problem should not be reduced to the problem of "correction" of solution obtained through deterministic approach since extremums of probabilistic objectives may substantially differ, by design parameters, from extremum of deterministic objective.**

So, we need to set up a RDO task in full stochastic statement with the involvement of probabilistic objectives (see Fig. 3). The optimization software must be capable of solving multi-objective optimization tasks and the solution of RDO task is a trade-off compromise Pareto-set between the efficiency indexes and probability indexes.

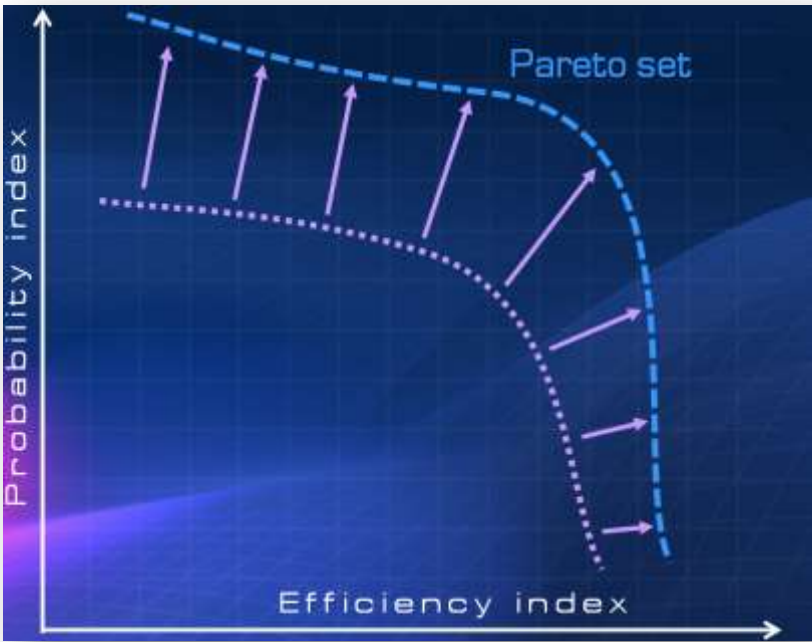

Fig. 3 The statement of multiobjective RDO task

The problem occurring while solving robust design optimization tasks is determining of probabilistic objective values. There exist various approaches. The simplest and the most universal and reliable method of evaluation of probabilistic objective is the Monte-Carlo method. The main advantage of this method, as applied to RDO problems, is no necessity of setting of any a priori assumptions about the goal function peculiarities (smoothness, monotony, continuity, differentiability, and so forth). However the true Monte-Carlo method requires dozens of thousands of your model simulations during optimization and is absolutely inapplicable in case when one uses full 3D CFD models. For this case we use our multilevel optimization scheme.

Automatic IOSO Multilevel Optimization Scheme for RDO Tasks

The typical situation, while solving a problem of optimization of complex engineering systems, is that the user has several tools of various degree of fidelity to perform the analysis. These tools differ according to their levels of complexity of modeling the actual physical phenomena and their different levels of numerical accuracy. The high-fidelity tools could be represented by detailed non-linear mathematical models of the researched systems (for example 3D CFD simulations) or even by the experimental samples of such systems. However, the use of such tools in optimization is associated with significant time expenditures. The low-fidelity (surrogate) models also allow carrying out optimization search, but the reliability of the obtained results can be rather low. Therefore, within the framework of the development of RDO methodology for complex systems, our method is based on a combination of various fidelity analysis tools. The objective here is to offer a procedure of multi-objective optimization of complex systems based upon the adaptive use of analysis tools of various levels of complexity. The intention is to minimize the solution time of optimization problem. This approach ensures the possibilities to search Pareto-optimal set of solutions, and also ensures the improvements of the surrogate mathematical model. The simplified scheme of work for the multilevel optimization procedure can be represented as follows (see the Fig. 4):

I. Building of low-fidelity (surrogate) model on the basis of data set previously obtained by high-fidelity analysis tool.
II. Solving the multi-objective optimization problem based upon a surrogate model.
III. For the obtained Pareto-set the objectives and constrained parameters are updated using the high-fidelity analysis tool.
IV. The refinement of the surrogate model is performed.
V. Replacement of the surrogate model and the return to step II).

The information stored during the search is used to improve the surrogate models. However, this model is correct not for the entire initial search area but only for a certain neighborhood of the obtained Pareto-set. This ensures purposeful improvement of approximating properties only in the area of optimal solutions that noticeably reduce the computing effort to construct surrogate models.

It is important to mention that from our point of view popular methods of one-shot construction of surrogate models are insufficient for real-life problems.

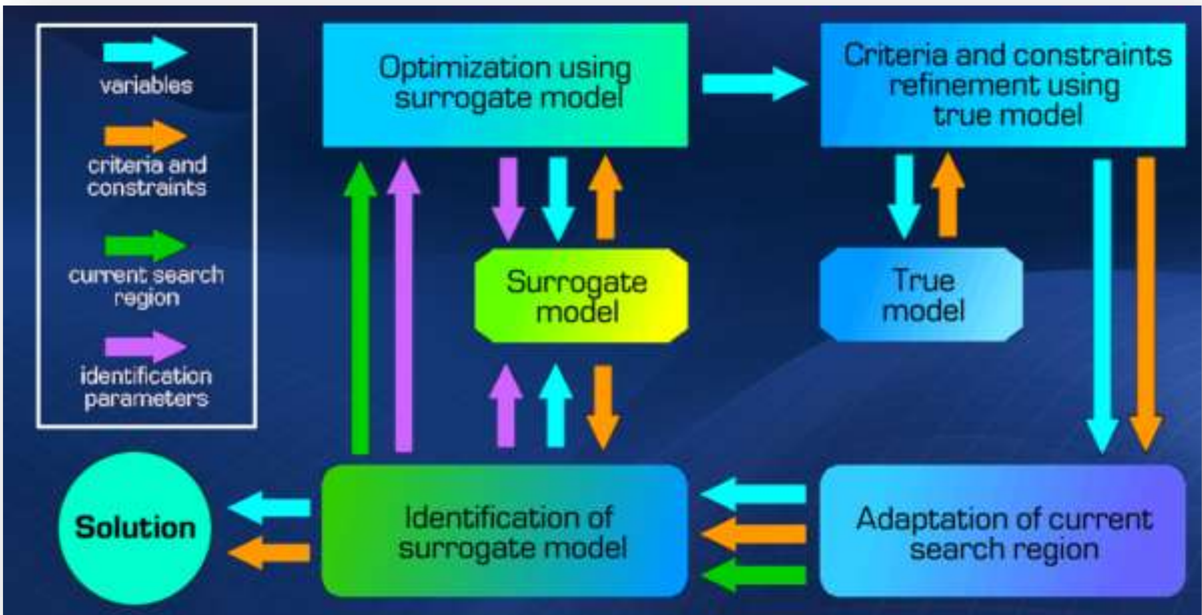

Fig.4 Multilevel IOSO Scheme

IOSO design optimization software by Sigma Technology is used as an optimizer in this methodology. Approx software by Sigma Technology is used for the construction of adaptive surrogate models. The main features of Approx surrogate model construction software:

1. Building of surrogate models for functional dependencies data, where float-type parameters depend on up to 80 float-type arguments.
2. Making it possible to call a “fast” surrogate models instead of time-consuming simulation applications.
3. Additional functions (response surfaces data loading/saving, mean error analysis, batch tasks support etc)

RSM technologies used:

1. Regression approaches, based on the Least Squares Method, providing free selection of resulting polynomial structure (presence of constant, linear, covariance or square terms) and adaptive transformation of arguments values;
2. Modified regression model expanding the set of arguments by means of adding transformed variables and selecting optimum structure of the polynomial;
3. Radial-basis functions techniques,
4. Weighted approximation
5. Neural networks.
6. Krigging.

Conclusion

Our RDO approach is a multiobjective optimization approach offering a compromise trade-off between the efficiency indexes and probability indexes as a result. It implies the automatic usage of various fidelity models (3-D CFD simulation as a high-fidelity model and an adaptive surrogate model as a low-fidelity model). The involvement of adaptive surrogate model allows a user to sufficiently increase the solution speed of RDO problem in full stochastic statement and makes it possible to handle it in the appropriate time limit without the use of extraordinary hardware resources.

REFERENCES

[1] Egorov, I.N., Kretinin, G.V. and Leshchenko, I.A. "How to Execute Robust Design Optimization", 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 04 - 06 Sep. 2002, Atlanta, Georgia.
[2] I.N. Egorov, “Optimization of a multistage axial compressor. Stochastic approach”, ASME paper 92-GT-163, (1992).
[3] I.N. Egorov and G.V. Kretinin, “Optimization of gas turbine engine elements by probability criteria”, ASME paper 93-GT-191, (1993).
[4] Y.-T. Wu, “Methods for Efficient Probabilistic Analysis of Systems with Large Numbers of Random Variables”, AIAA-98-4908, Proceeding of 7th AIAA/USAF/ NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, St. Louis, USA, (1998).
[5] R. Yokoyama and K. Ito, “Robust Optimal Design of a Gas Turbine Cogeneration Plant Based on Minimax Regret Criterion”, ASME paper 99-GT-128, (1999).
[6] S.M. Batill, J.E. Renaud and X.-Y. Gu, “Modeling and Simulation Uncertainty in Multidisciplinary Design Optimization”, AIAA-2000-4803, Proceedings of 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Long Beach, USA, (2000).
[7] J. Marczyk, “Stochastic Multidisciplinary Improvement: Beyond Optimization”, AIAA-2000-4929, Proceedings of 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Long Beach, USA, (2000).
[8] M.T. Tong, “A Probabilistic Approach to Aeropropulsion System Assessment”, ASME paper 2000-GT-0001, (2000).
[9] I.N. Egorov, G.V. Kretinin, S.S. Kostiuk, I.A. Leshchenko, and U.I. Babi. “The methodology of stochastic optimization of parameters and control laws for the aircraft gas-turbine engines flow passage components”, ASME J. Engineering for Gas Turbines and Power, 123:495–501, (2001).
[10] I.N. Egorov, G.V. Kretinin, I.A. Leshchenko, “Stochastic Optimization of Parameters and Control Laws of the Aircraft Gas-Turbine Engines – a Step to a Robust Design), Elsevier Science Ltd, “Inverse Problem in Engineering Mechanics III”, pp.345...353, (2002).
[11] J.M. Wallace, S. Wojcik and D.N. Mavris “Robust Design Analysis of a Gas Turbine Component”, ASME paper GT2003-38546, (2003).
[12] N. Lecerf, D. Jeannel and A. Laude, “A Robust Design Methodology for High Pressure Compressor Troughflow Optimization”, ASME paper GT2003-38264, (2003).
[13] V.E. Garson and D.L. Darmofal, “On the Aerodynamic Design of Compressor Airfoil for Robustness Under Geometric Uncertainty”, – ASME paper 2004-GT-53581, (2004).