Robust Multiphysics Optimization of Fan Blade

K. Vinogradov, G. Kretinin and I. Leshenko

Introduction and Task Statement

One of the most relevant tasks is the fan blade robust multiphysics optimization under geometrical uncertainties. A modern civil aircraft fan blade is considered as an investigation object. The blade must provide high level of the aerodynamic efficiency (adiabatic coefficient of efficiency) and necessary structural properties. The fan blade flutter phenomenon sensitivity is also considered. Computational model of the fan blade for test case IC-04 includes blade solid domain and air path. CAD model of the blade profile is presented in Fig. 1. From enormous number of calculations necessitates to solve multiphysics robust optimization problem task statement with one blade was chosen. In aerodynamic calculations only blade profile is modeled. In the strength calculations, full blade (with foot) is considered. Blade foot has no geometrical uncertainties and variable parameters and is not involved in optimization procedure (nominal geometry). Computational aerodynamic model of the fan blade is presented in Fig. 1. NUMECA AutoBlade 8.9.1 was used as parameterization software to construct computational mesh and to automatize meshing and aerodynamic calculations procedures. Simplified parameterized blade model in NUMECA AutoBlade is also present in Fig. 1. The next cross sections were considered: 0, 30, 50, 70, 85, 100% of the normalized blade height.

Computational mesh provided for this test case IC-04 consists of the two parts. For CFD aerodynamic calculations, hexahedral structured mesh is used. To generate this type of mesh, NUMECA AutoGrid5 is used. The number of nodes for aerodynamic calculations is 1 300 000 nodes. Aforementioned number of nodes was chosen based on preliminary grid dependency test at the same aerodynamic

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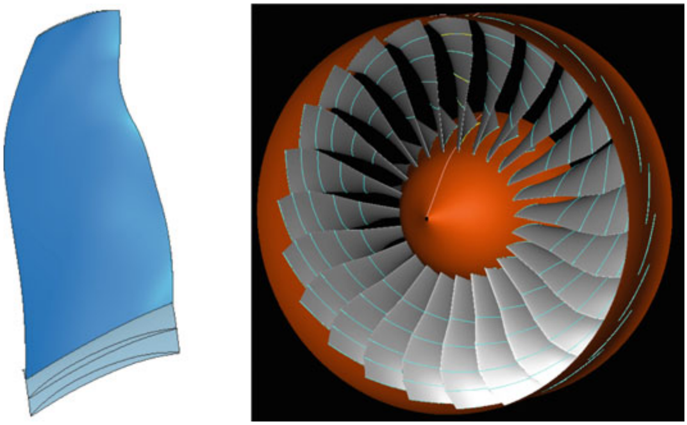


Fig. 1 Computational model for aerodynamic calculations

calculations for other fan and compressor blades. Chosen mesh has growth ratio 1.5 and the first cell size 5–6 m. "H–O–H" topology of the computational mesh was used because this mesh type provides high mesh quality level and necessary computational time.

To carry out strength analysis and to determine mode of deformation hexahedral combined (structured/unstructured) mesh also was used. To generate this type of mesh, ANSYS Mechanical Meshing was used. The number of nodes for strength analysis is approximately 100 000 nodes. Aerodynamic mesh of the fan blade is presented in Fig. 2. Mesh for structural analysis is also presented in Fig. 2.

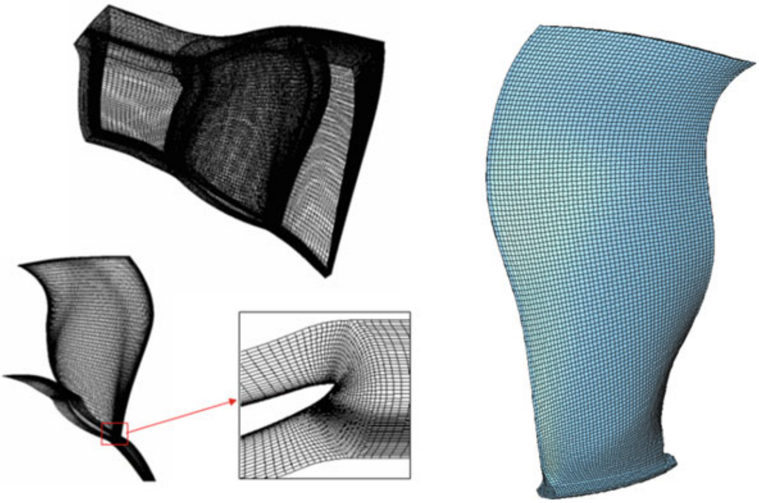


Fig. 2 Computational mesh for aerodynamic and structural calculations

Total pressure and total temperature in stationary frame were used as inlet boundary conditions. The flow direction is set by dimensionless angle components. Boundary conditions for aerodynamic calculations are set in accordance with standard atmosphere conditions. To couple parameterized blade profile and constant blade foot specify technology in ANSYS Mechanical APDL was developed. By means of additional curves and surfaces sketching, we can construct intermediate blade part between profile and foot in hub blade cross section for different stagger angles. Visualization of this procedure is present in Fig. 3.

Analysis of fluid flow and film cooling has been performed using NUMECA FINE/Turbo [1] which employs a structured grid system. The solutions have been obtained using the finite volume method to discretize the compressible RANS equations. The Spalart–Allmaras turbulence model is used as a turbulence viscosity equation solving and closure system of equations. The boundary conditions at the outlet of the computational model (radial distributions of pressure were accepted according to the preliminary aerodynamic calculations at the operating point, near the stall margin and in other areas of interest. One of the key features of aerodynamic calculations and optimization task statement is the one optimization iteration corresponds to five aerodynamic calculations (operating point-95% of Speed, 80% of speed to flutter sensitivity, and three points to determine stall margin in automatic mode). Deterministic optimization task statement of the FSI multiphysics problem is presented in the section "General Robust Design Optimization Task Statement".

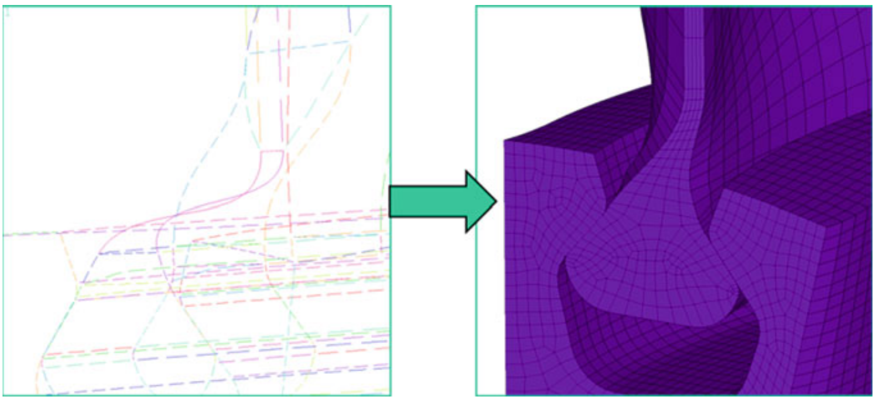


Fig. 3 Intermediate blade part between profile and foot

Geometrical Uncertainties Considered

In the proposed test case, huge number of geometrical uncertainties was considered. There are geometrical uncertainties from fan blade manufacture tolerances and deviations. Scheme of the considered blade sections location and scheme of the main geometrical uncertainties considered (red circles) in blade section are presented in Fig. 4.

Red circles show cross sections chose for providing uncertainties and further UQ investigations. The main uncertainties considered as it is shown in Fig. 5 are blade thicknesses in different profile locations (at 3 mm from leading and trailing edges (e1, e2), and 20 mm from leading and trailing edges (e3, e4) and maximal blade thickness in section (E). Profile angle of incidence is also taking into consideration.

General information example for the considered geometrical uncertainties is presented in Table 1. In this table, main statistic parameters (mean value, variance, and distribution law) for probability density function description are presented. Geometrical uncertainties are presented by means of deviations from nominal fan blade dimensions. Nominal fan blade dimensions were obtained from CAD model of the fan.

Example of the theoretical graphs of the probability density functions in comparison with experimental bar graphs for presented uncertainties is shown in the Fig. 5.

Analysis of probability density function graphs for considered geometrical uncertainties showed most of experimental stochastic parameters can be described by means of Gaussian pdf distribution law with acceptable accuracy level. Some parameters will have to be described by means of lognormal and beta distribution.

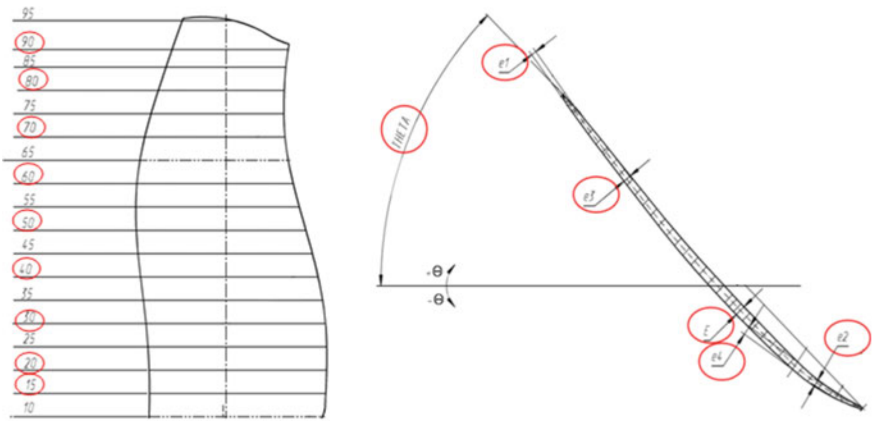


Fig. 4 Scheme of the considered blade geometrical uncertainties

Table 1 Example of general information about geometrical uncertainties

Name of the uncertainty	Mean value	Variance	Law of distribution
ΔE15	−0.0896	0.079	Gaussian
ΔTHETA15	−0.4239	4.9772	Gaussian
Δe2_15	μ = −1.199	σ = 0.302	Lognormal

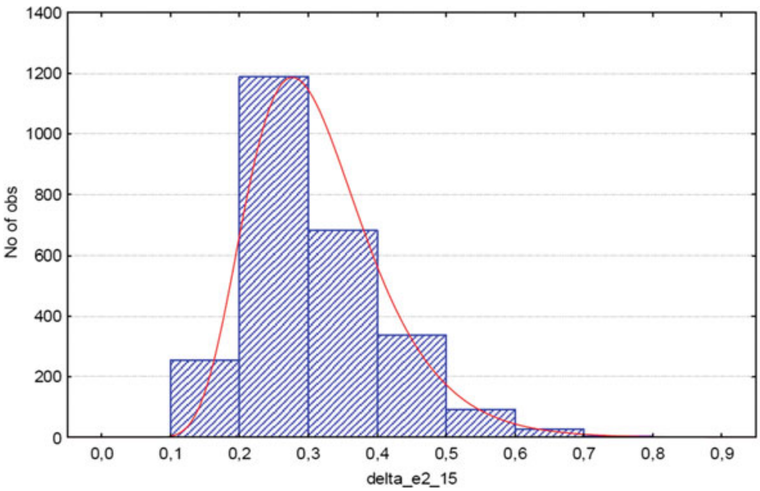


Fig. 5 Theoretical pdf example in comparison with experimental bars

General Robust Design Optimization Task Statement

Let us consider mathematical formalization of the RDO problems. While creating a technical system, the designers are to form the vector of values of system efficiency $y = (y_1, y_2, \ldots, y_m)$, which are to be maximized, minimized, and constrained, to form the vector of variable parameters $x = (x_1, x_2, \ldots, x_n)$, varying of which leads to the variation of the efficiency, and to form the vector of external conditions $e = (e_1, e_2, \ldots, e_k)$. The correlation between these vectors as $y = f\,(x,\ e)$ forms the mathematical model of the system under investigation. The existence of a mathematical model makes it possible to formulate a design problem as an optimization task, which lies in the search of one or several vectors $x^* \in D$ that ensure the best (in some way) efficiency. Here

$$D = \{x \in R^n \,|\, x_{j-} \le x_j \le x_{j+1},\ j = 1,\ \ldots, n;\ g_i(x,\ e) \le 0,\ i = 1, \ldots, w\} \qquad (1)$$

is the search region, $g_i(x, e)$ is the constrained efficiency values. Such an "ideal" design problem statement was regarded, until recently, as a necessary and sufficient condition to obtain an optimal design. In practice, however, such an approach of solving real-life tasks deals with serious problems connected with impossibility to implement optimal project solutions. The main reason for this lies in the existence of a large number of uncertainties, which are not taken into account while modeling the system, optimization problem statement, and solving procedure.

The attempt to include uncertainties in design problem formalization results in the necessity to consider relations: $x = x(\bar{x},\ \xi_x)$; $e = e(\bar{e}, \xi_e)$, where $\bar{x},\ \bar{e}$ are the ideal vectors of variable parameters and environmental conditions; $\xi = (\xi_x,\ \xi_e)$ corresponds to the vector of random values including the uncertainties in implementation of variable parameters and environmental conditions. Generally, to solve a RDO problem one must be able to determine system efficiency values $y = f(x,\ e)$ for given values of $\bar{x},\ \bar{e}$, and hence to know the laws of distribution of vector components ξ [2]. In our situation, we consider aforementioned geometrical uncertainties (blade thickness) in five cross sections of the blade. These parameters are the stochastic values, which distribution laws were obtained as a result from the experimental data and are shown (as example) in Fig. 5. Blade leading edge and trailing edge angles as to stagger angle were set as variable parameters in parameterization model. Total number of variable parameters and uncertainties are 42. As a probabilistic criteria were used efficiency values with probability no less than one given (P = 90%).

The main problem occurring while solving robust design optimization problem is determining probabilistic criteria values. The simplest and the most universal method of evaluation of probabilistic criteria 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 on). However, the efficiency of the Monte Carlo method when solving real-life problems to a great extent depends on the required accuracy of definition of probabilistic criteria. Particularly, applying the gradient methods of optimization, requiring high accuracy of definition of probabilistic criteria, resulting in high computational expense (required number of tests at each iteration of extremum search makes up $\approx 10^6 - 10^9$). The second approach includes a number of methods which are based on different approximation techniques (Taylor's series, response surfaces, and so on). In this approach, results of response surface modeling algorithms (surrogate models) are used for probabilistic criteria evaluation. When solving the task under consideration, we used the Monte Carlo method along with the method of multicriteria optimization IOSO [3] as well as the procedure of multilevel optimization involving surrogate models [1–7].

Deterministic Optimization Results

To solve deterministic optimization task, aerodynamic and stress/flutter sensitivity computations in NUMECA FINE/Turbo and ANSYS Mechanical APDL were carried out in one software loop. Deterministic optimization results were used as initial DoE to further robust optimization process (to construct surrogate model for

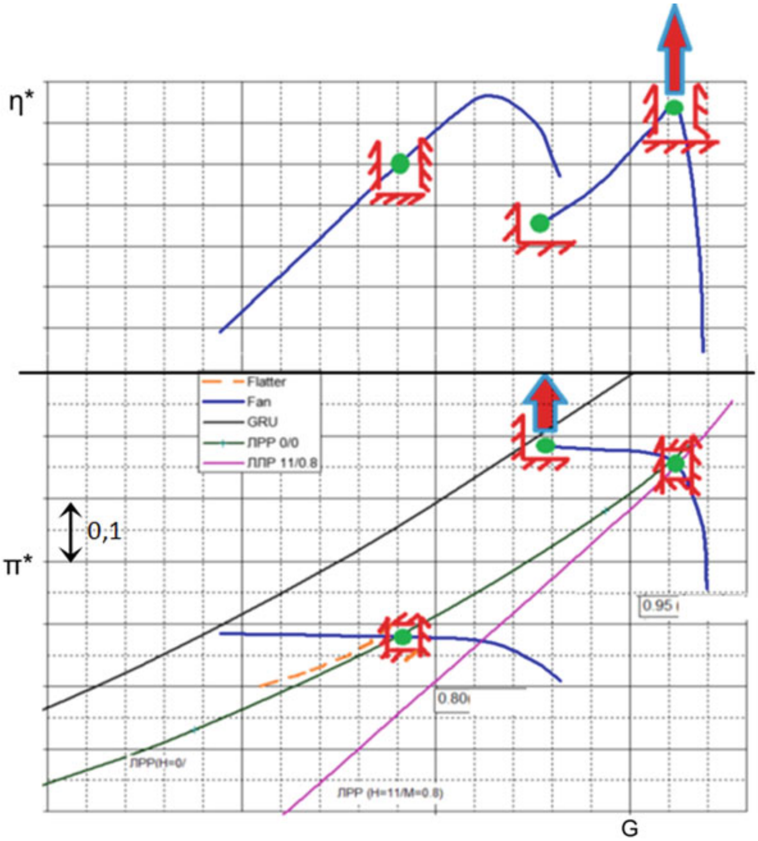


Fig. 6 Task statement

robust optimization in iterative procedure). Necessary information about deterministic optimization task statement is presented in Fig. 6.

Some additional details about deterministic optimization are presented below.

Objective functions:

- increasing of the aerodynamic efficiency at rotating speed n = 0.95;
- increasing of the stall margin at rotating speed n = 0.95 (no less than 0.1);
- decreasing maximal static stresses in blade profile;
- decreasing flutter sensitivity across TBC criterion (Torsion-bending coupling).

Constraints: compressor pressure ratio, mass flow at rotating speed n = 0.95, n = 0.8

Variables: camber line form (blade LE and TE angles), stagger angle in six sections.

TBC criterion is the experimental-based dependence between torsion and bending displacement by first flexion mode for leading edge and trailing edge control points.

Scheme of the TBC criterion calculations and necessary mathematical equations is presented in Fig. 7.

Based on aforementioned task, statement and details more than 2500 iterations of the deterministic optimization were carried out. Essential improvement for all criteria considered was obtained as a result of the optimization. Aerodynamic efficiency was improved on 1%, stall margin improvement was 0.75, and equivalent von Mises stress (sstt) was decreased on 42%. We selected four points with maximal levels of criteria considered. Comparison between aerodynamic and multi-physics optimization is presented in Fig. 8. Figure 8 shows that the results of aerodynamic optimization have a much higher level of aerodynamic efficiency and stall margin (D_Ky) but poor structural properties (static stresses in the blade profile and flutter sensitivity are too high (TBC > 0.3)). Such structural properties make the blade non-viable. The results of deterministic multiphysics optimization are represented with yellow triangles and show worse aerodynamic characteristics (by 0.9% of aerodynamic efficiency) than the results of aerodynamic optimization. At the same time, they show much higher structural characteristics. In particular, level of von Mises stress on 35–40% less, flutter sensitivity is TBC < 0.22. The results of

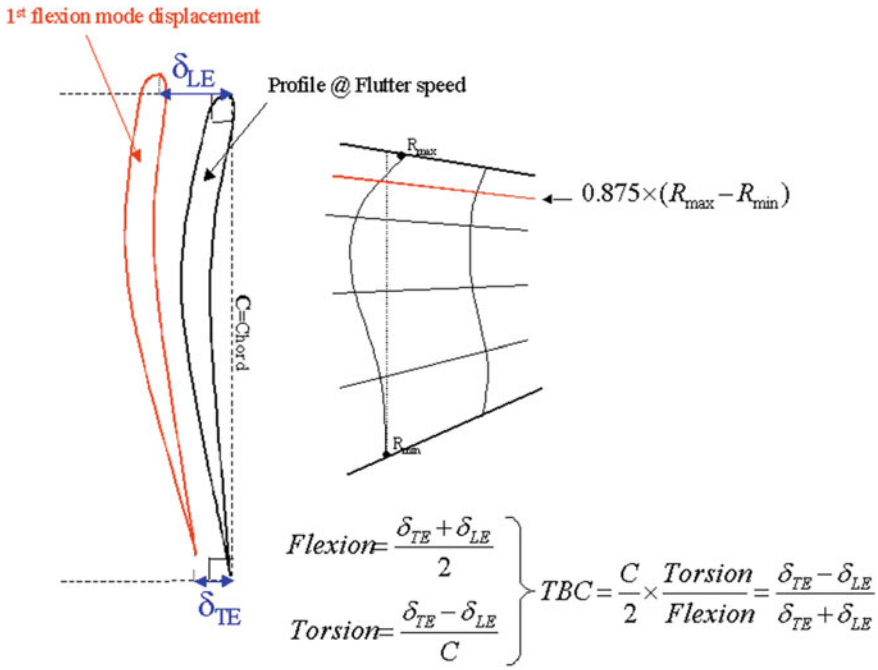


Fig. 7 TBC criterion formulation

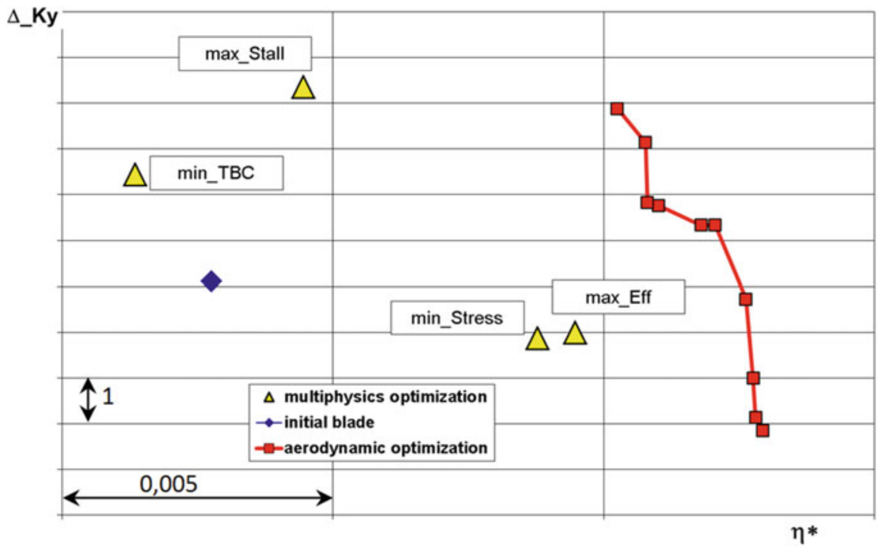
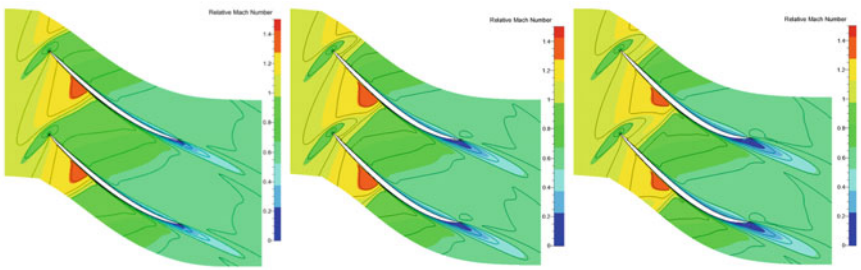


Fig. 8 Comparison between aerodynamic and multiphysics optimization

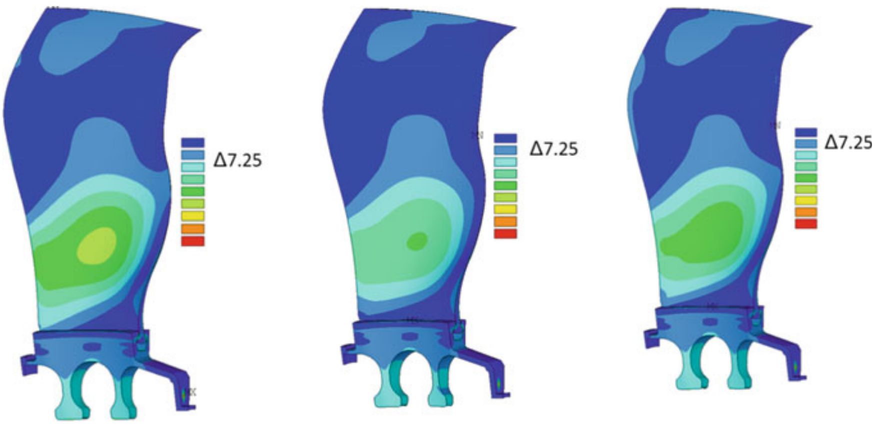
the multiphysics optimization have the essential difference in all criteria considered (aerodynamic efficiency difference is 0.8%, stall margin difference is 4–5%, and different stress level (max difference 15–19%). The results of this comparison prove the necessity of multiphysics optimization. Some of the aerodynamic characteristics of the results of deterministic multiphysics optimization are presented in Fig. 9. Structural characteristics of the fan blades (distribution of the von Mises stress) for the results of deterministic multiphysics optimization are presented in Fig. 10 that show that substantial differences in the level of maximal stress are present between all of represented blades.

Thus, the problem of multiphysics optimization of the fan blade (aerodynamics + strength + flutter sensitivity) in the deterministic approach has been solved.



(a) Initial blade (b) Max efficiency (c) Min stresses

Fig. 9 Flow patterns in span 50% in operating point for some results



(a) Max efficiency (b) Min static stress (c) Min flutter sens.

Fig. 10 3D stress code results (static stress in the fan) for some multiphysics optimization results

Pareto sets for all four criteria under consideration were obtained. Results of deterministic optimization were used as initial DoE for the robust optimization problem.

Multilevel Robust Design Optimization Using Surrogate Models and IOSO Technique

In the present work, Approx software [8] is used for the surrogate model construction. This software allows us to obtain different types of the surrogate models: from full-square regression models [9] to different types of artificial neural networks.

The central point during construction of the surrogate model is the choice of the structure of the approximating function. Models based on linear regression with the function parameters defined as:

$$Par = K_0 + \sum_{i=1}^{N} K_i \cdot m_i \tag{1}$$

where K0, Ki—regression coefficients.

Within this work, due to the large number of the problem parameters, it was decided to use modified method of least squares with an extended set of variables.

The approach is based on full-square regression with the regressors formed on an extended set of variables. The extended set of variables is comprised not only of the variables themselves but also of their functional dependencies. Number of regressors might end up very large, so the algorithm uses adaptive selection of only those regressors that represent the response surface the most fully. Tuning of the

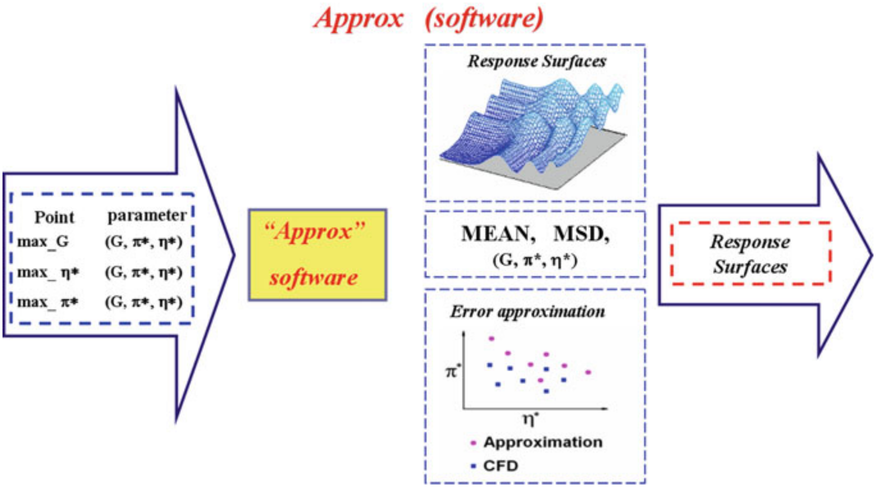


Fig. 11 Surrogate model creating scheme in Approx software

parameters of the response surface of this kind takes into account as many of the regression coefficients as possible, as well as the relative accuracy achieved by the adaptive selection procedure. The higher is the number of the regression coefficients the more accurately the starting points can be described. Scheme of the surrogate model construction in Approx software is presented in Fig. 11. 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 nonlinear mathematical models of the researched systems 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, the methods based on the combination of various fidelity analysis tools are widely practiced.

The objective here is to offer the procedure of multiobjective optimization of complex systems based on the adaptive use of analysis tools of various levels of complexity. The intention is to minimize the use of high-fidelity time-consuming tools for the analysis. This approach ensures the possibilities to search Pareto-optimal set of solutions and also ensures improving the surrogate mathematical model.

The simplified scheme of work for the multilevel optimization procedure can be represented as follows (Fig. 12).

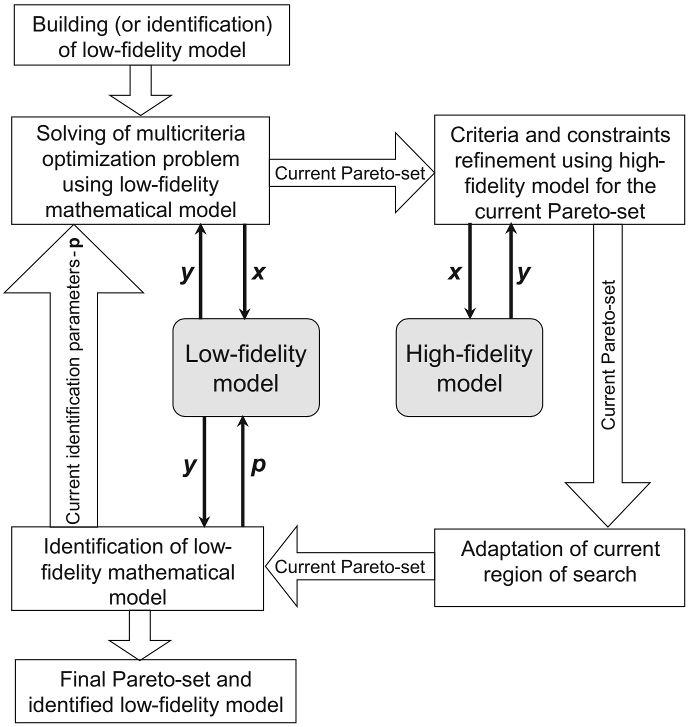


Fig. 12 Scheme of multilevel optimization procedure via IOSO NM software

- Generation of surrogate model on the basis of the data set previously obtained.
- Solution of the multiobjective optimization problem based on a surrogate model. Updating of the objectives and constrained parameters obtained for the Pareto set using the high-fidelity analysis tool.
- Refinement of the surrogate model.
- Replacement of the surrogate model and return to step II.

The particular features of the problem define the number of iterations for such a multilevel procedure. The number of applications of high-fidelity analysis tools is limited to the product of the number of iterations and the number of Pareto-optimal solutions. Interaction between Approx software and IOSO optimization algorithm is presented in Fig. 13.

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. In this approach, results of response surface modeling algorithms (surrogate models) are

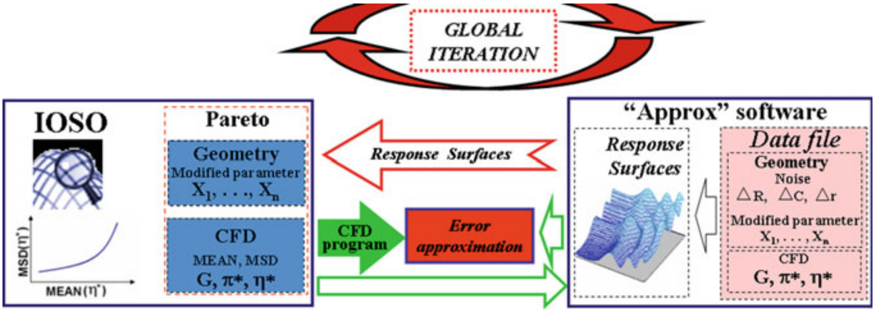


Fig. 13 IOSO NM interaction algorithm with surrogate model

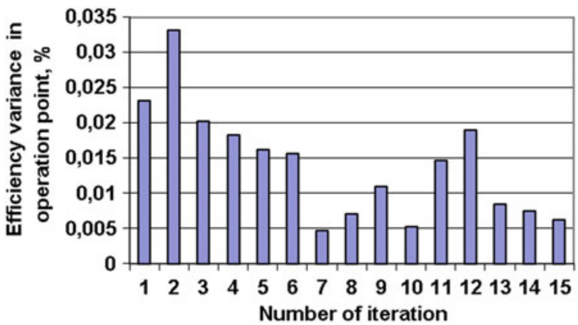
used for probabilistic criteria evaluation. In our case, uncertainty quantification and robust optimization tasks are solving together.

RDO Results for Fan Blade

Surrogate model construction for RDO procedure.

At the first step, initial DoE based on deterministic optimization results was constructed. To generate initial combinations of the variable parameters deterministic optimization task was solved. Within the applied procedure of multilevel optimization, 15 global iterations were carried out. Initial design of experiments has 1400 calculations based on deterministic optimization results. Additional 25–50 calculations (high-fidelity CFD simulation) at every multilevel iteration of the optimization were carried out. Total number of calculations in database to construct surrogate model was ≈500. Variations of accuracy of low-fidelity models via iterations are shown in Fig. 14. The tendencies for all criteria considered are noticeable toward increase of low-fidelity model accuracy under the growth of the number of iterations. It should be noted that the worse accuracy of approximation has the maximal value less than 2% (for TBC criterion).

Fig. 14 Surrogate model accuracy modifications (aerodynamic efficiency)



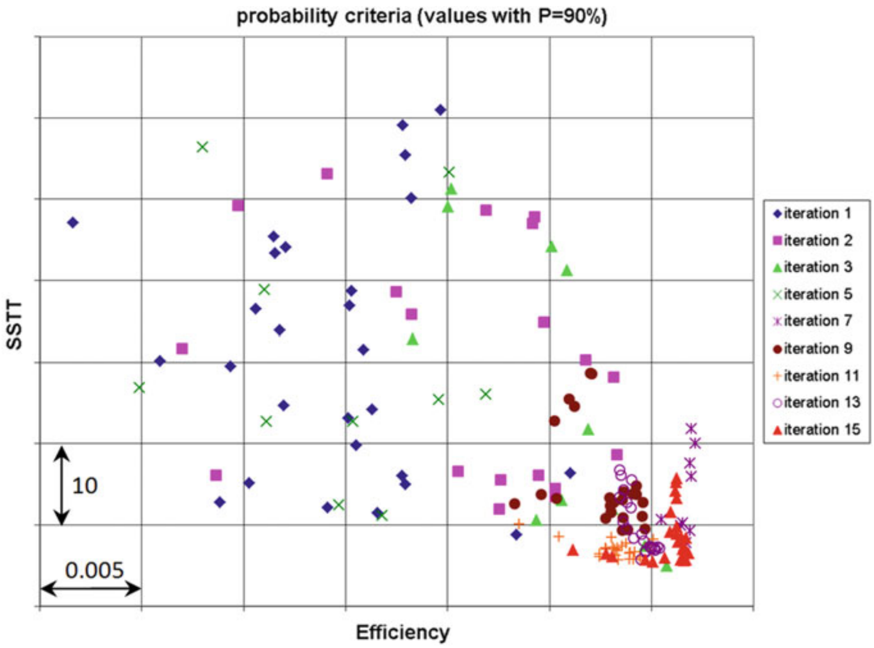


Fig. 15 Surrogate model database modifications for aerodynamic efficiency and static stress

The next accuracy levels were obtained:

- 0.3% for mass flow rate$
- 0.006% for aerodynamic efficiency
- 0.015% for stall margin
- 1% for static stress
- 1.8% for TBC criterion.

During iteration refinement of the surrogate model, substantial nonlinearity in the change of the model accuracy was observed which was caused by the high dimensionality of the problem (42 parameters). In spite of aforementioned problems, obtained surrogate model can provide necessary level of prediction accuracy to carry out robust optimization based on these results. Overview of the optimizing search during robust optimization on probabilistic criteria (efficiency and strength with 90% confidence) for some of 15 multilevel iterations is shown in Fig. 15. The figure shows clear tendency for the aerodynamic efficiency to increase and for the maximal stress to decrease during the robust optimization.

As a result, evident Pareto set between aerodynamic efficiency and structural properties has formed on the 15 iterations. It has a pronounced corner point. In addition, the search dynamic demonstrates the influence of complexity and multi-physicality of the problem on the obtained result.

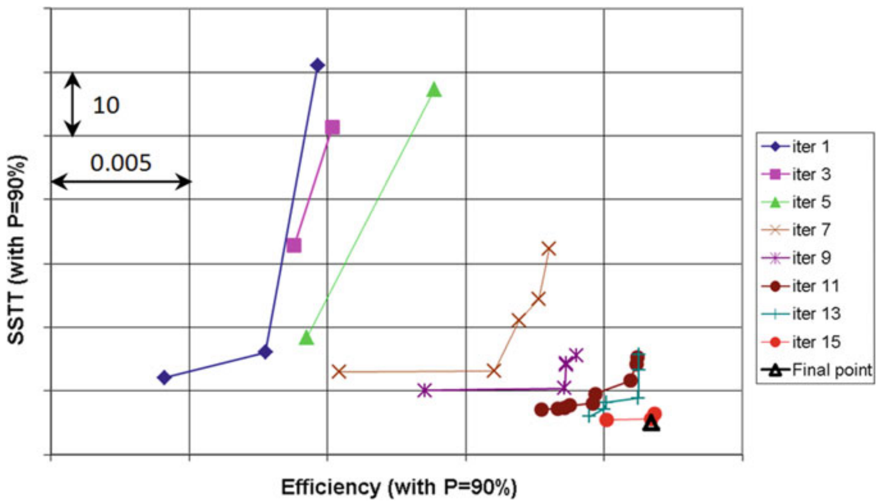


Fig. 16 Pareto set (between aerodynamic efficiency and static stress) modifications via multilevel iterations of robust optimization

Dynamic of the change of the Pareto set between aerodynamic efficiency and structural properties during multilevel iteration of robust optimization is presented in Fig. 16. Figure 16 shows tendency for the values of probabilistic criteria to improve. For example, for efficiency with P = 90% the gain was about 1.4% and for maximal stress the reduction was 19%. This result demonstrates high efficiency of the developed and employed technology for the robust optimization problems of high dimensionality. As a final result of the optimization, according to the traditional rules of the Pareto set analysis, the "angle point" corresponding to the best aerodynamic efficiency and structural properties was used.

The probability density distribution of the aerodynamic efficiency for deterministic and robust optimization results is presented in Fig. 17. The chart clearly demonstrates the achieved improvement. During the initial stages of the robust optimization, the deterministic and the mean values of a criterion had worsened but eventually (on the fifteenth iteration) there was a significant gain in the mean value of efficiency, decrease in its variance (from $\sigma = 0.08$ to $\sigma = 0.059\%$), as well as an increase in the probabilistic criterion up to $\Delta\eta_{90\%} = 0.15\%$.

The probability density distribution of the structural properties (static von Mises stress) for deterministic and robust optimization results is presented in Fig. 18. The tendencies for the distributions are similar to the ones for the aerodynamic characteristics. The results of the deterministic optimization have the highest mean value and probabilistic criterion ($SSTT_{90\%}$) for the static stress. During the initial stages of the robust optimization, the mean value of the stress as well as its variance had decreased. On the fifteenth iteration, further significant decrease of the mean value of the stress, its variance (from $\sigma = 1.362$ MPa to $\sigma = 0.982$ MPa), and a decrease in the probabilistic criterion were obtained. The probability density

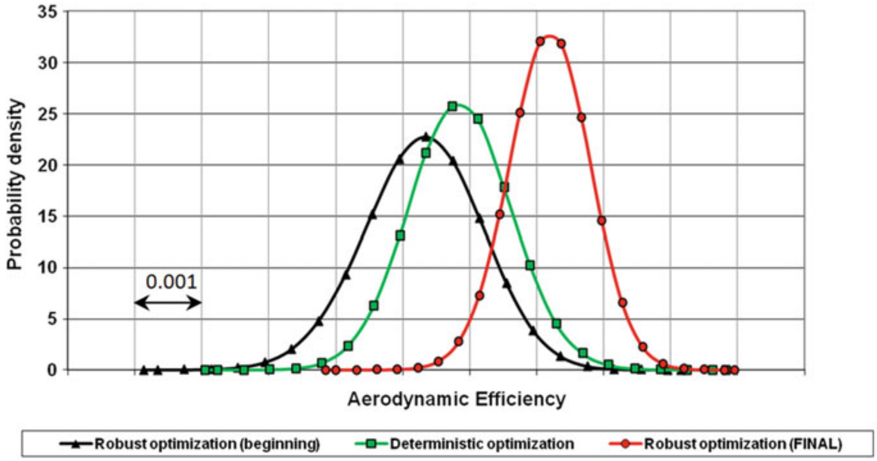


Fig. 17 Pdf for deterministic and robust optimization results (aerodynamic efficiency)

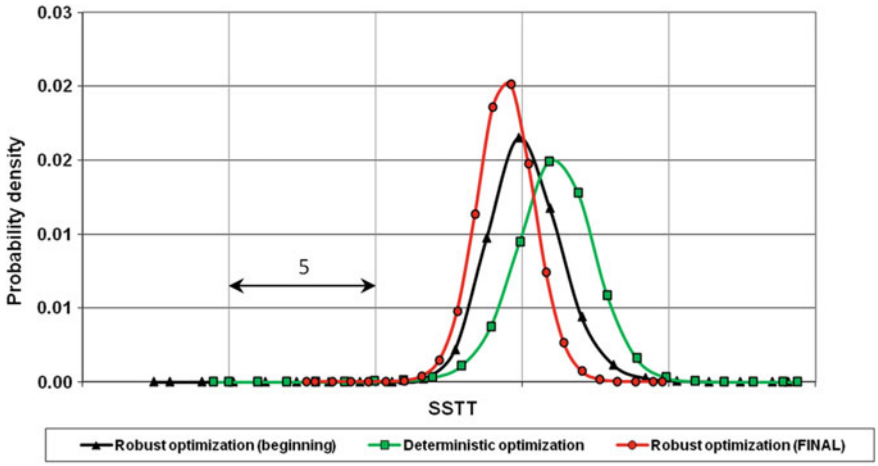


Fig. 18 Pdf for deterministic and robust optimization results (structural properties)

distribution of the stall margin for deterministic and robust optimization results is presented in Fig. 19. The results of the deterministic optimization have the highest mean value and probabilistic criterion ($D\_Ky_{90\%}$) for the stall margin, which was caused differences in the task statement of the deterministic and robust optimization. The deterministic optimization was supposed to maximize the stall margin but for the robust optimization it was used as a constraint. During the initial stages of the robust optimization, the mean value had decreased while the variance had increased significantly. By the fifteenth iteration, the mean value had not changed

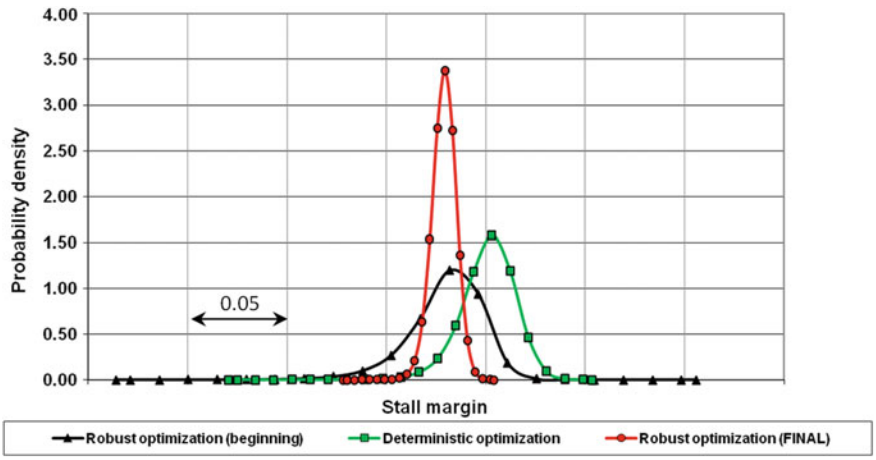


Fig. 19 Pdf for deterministic and robust optimization results (stall margin)

much while the variance had decreased significantly (from σ = 1.3 to σ = 0.6%). Thus, the results of robust optimization can guarantee a probabilistic constraint on the stall margin.

Conclusions

1. One of the most promising techniques to solve RDO problems in coupling is usage of approximate assessments of probabilistic criteria under Monte Carlo combined with direct optimization techniques IOSO.
2. Application of the multilevel optimization procedure offers a significant reduction of the computing time expenditures for the solution of complex real-life problems while maximizing the probability of manufacturing the object under study.
3. Deterministic multiphysics optimization of a fan blade has been carried out. The fan aerodynamic efficiency has been increased, the maximal stress in the blade profile, and flutter sensitivity has been decreased. Pareto sets were constructed from the results of the deterministic optimization.
4. The problem of the robust optimization of a fan blade under the influence of geometrical uncertainties (deviations of manufacturing) has been stated and solved by means aforementioned technique. The total number of parameters was 42.
5. From the results of the robust optimization a point from a Pareto set has been obtained which can provide maximal efficiency, minimal stress in the blade profile and the necessary level of the stall margin and the flutter sensitivity with the 90% probability. Furthermore, during the robust optimization the variance of

the aerodynamic and the structural properties caused by the geometrical uncertainties has decreased. The variance has decreased on average from 1.3 to 0.6%.

6. The results show high efficiency of using the developed approach for the robust optimization problems with a high number of geometrical uncertainties.
7. The objectives of the further research will be the increase in the number of the optimization criteria and the uncertainty quantification in the blade foot and also the direct simulation of vibro-stress in the blade (two-way FSI) during the robust optimization.

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