MULTIPOINT AERODYNAMIC TRANSONIC SHAPE OPTIMIZATION BY MEANS OF ACCELERATED GENETIC ALGORITHM

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Abstract

A new hybrid genetic algorithm has been developed by the authors to solve multi-point/multiobjective optimization problems in high dimensional space of design variables. The idea behind the method is to use simultaneously the numerical models of different complexity and perform the bulk of computations basing on a less time-consuming low-fidelity model, while only a small fraction of the computations is performed using a high-fidelity model to check the most promising designs and refine the quality of an approximate concept. As a result, the computational accuracy corresponds to the more precise model, and total computational burden is reduced by several times as compared to a conventional genetic algorithm. Different low-fidelity models were tested during the study and coarse grid calculations were chosen as the most simple and reliable technique. Several three-dimensional transonic aerodynamic design problems are addressed in the paper, including the aerodynamic design of a regional jet, medium-haul passenger aircraft and an advanced high-speed long-haul airliner.

Introduction

The development of modern aircraft requires numerous computations modeling each system behavior at different flight regimes. Aerodynamic design problems constitute a very significant part of these computational efforts. A number of design flight regimes rather than a single one should be taken into account by a designer. It is valid not only for maneuvering combat aircraft, but even for long-haul passenger airplane with the dominant cruise regime. Transonic regimes are of especial complexity for investigating numerically because of strong non-linearity of the governing equations, increased sensitivity of the flow to the viscous effects and a sharp change of the flow characteristics with small alteration of the flight conditions.

Optimization methods play a key role in the process of aerodynamic design enabling one to obtain a really effective configuration with good trade-off multipoint behavior. Taking into consideration aforementioned complexity of the analysis codes, the necessity to examine a lot of different alternatives and the stringent overall design time constraints the requirements on the optimization methods utilized are extremely high. Besides, the quality of optimization demands close attention due to the strong competitiveness of today's aircraft sales situation, when a few percent increase in the aircraft performance can play a decisive role in a market preference [1].

While many new robust optimization methods such as genetic algorithms (GA) [2-6] have been developed recently for deal with non-smooth, multimodal and "noisy" objective functions the problem of their effective utilization remains vitally important because of the hindering the optimal design search by the huge amount of the analyses needed. To that end, researches try creating different GA's accelerating techniques [5,7-9], and the sound idea of using the models of different complexity is the very popular one [10-13]. These may be quite dissimilar approaches or different levels of approximations in the framework of the single approach. An example of dissimilar approaches in aerodynamics is using the panel methods and Navier-Stokes methods for low speed flow analysis. The utilization of the so called surrogates or metamodels [14,15] is an extreme manifestation of this technique. The different approximation levels can be exemplified by use of coarse and fine grids in the framework of the same method. As a rule, going to a more complicated model entails a significant increase in amount of computations. Genetic algorithms typically require thousands of direct analysis. When performing such computations with the use of a high-fidelity model, the computation time becomes unacceptably large. On the other hand, the use of low-fidelity models does not allow one a true optimum to be determined. Therefore the creation of a hybrid algorithm capable of operating alternatively with the models of different complexity is a logical solution. With the computational process well organized, it is hoped that the computer time may be considerably reduced as compared to the high-level optimization while retaining accuracy of high-fidelity model.

In the present work the hybrid optimization procedure is developed as applied to the genetic algorithm. The difference between two analysis fulfilled at fine and crude meshes is modeled by surrogate model – such an approach has been shown to be more general than the straightforward use of the surrogates [16,17]. The details of the algorithm and computational test examples are presented below.

Problem formulation and description of the optimization algorithm

Let there be an N-dimensional space of the design variables Xi, i=1,2,…,N, where an extremum of the objective function $F(\mathbf{X})$ is being sought. We make no assumptions regarding the behavior of the objective function; in particular it may be even discontinuous. It is assumed that there are two direct methods for computing the values of the objective function in the N-dimensional space: the accurate $F(\mathbf{X})$ and approximate $G(\mathbf{X})$ ones. Denote the difference between the objective function values $F(\mathbf{X})$ and $G(\mathbf{X})$ by $\Delta(\mathbf{X})$. The difference $\Delta(\mathbf{X})$ is assumed to be a continuous and sufficiently smooth function. Let us take a piecewise linear approximation for $\Delta(\mathbf{X})$ representation:

$$\tilde{\Delta}(\mathbf{X}) = \Delta(\mathbf{X}^k) + C^T \cdot (\mathbf{X}-\mathbf{X}^k) \tag{1}$$

where $\mathbf{X}^k$ is the nearest point ("node") at which both the accurate $F(\mathbf{X}^k)$ and approximate $G(\mathbf{X}^k)$ values of the objective function are known; C is the sought vector of linear form coefficients. To determine the coefficients Ci, we use the procedure of interpolation over the neighboring "nodes".

$$\tilde{\Delta}(\mathbf{X}^j) = \Delta(\mathbf{X}^k) + C^T \cdot (\mathbf{X}^j-\mathbf{X}^k), \quad j=1,2,\ldots N \tag{2}$$

For this system of linear algebraic equations to be well-conditioned, it is necessary that the system of vectors $\mathbf{X}^j-\mathbf{X}^k$ be linearly independent. Used in the present work is a genetic algorithm with a binary representation of the variables, that is, the space of design variables is discrete. With the space partition being discrete, the neighboring nodes often form a dependent vector system. Hence, to construct an independent system we use the well-known Gramm-Schmidt orthogonalization process. If in the process of the orthogonalization a certain vector $\mathbf{X}^j$-$\mathbf{X}^k$ turns out to be a linear combination of the preceding ones (that is, the orthogonal projection approaches zero), then this node is excluded from consideration and the next one is taken. Notice, that the Gramm-Schmidt orthogonalization process is equivalent to the reduction of a matrix to a lower triangular form and the linear form coefficients in a new orthogonal basis are determined immediately. For the verified values N≤100, the construction of the linear form presents no problems and takes less than 0.05 sec of the Pentium IV 2400 CPU. Similar to conventional genetic algorithm [2], basic operators of the hybrid GA are selection, crossover and mutation. The general optimization algorithm is as follows:

- selection of the design variables Xi, i=1,..,N and their variation ranges;
- random formation of NINITB ~ 4·N initial vectors ("nodes") for which the value of F, G and Δ are calculated;
- random formation of the initial population of NPSIZE = 2÷8·N vectors (individuals).

Next, the following actions are executed for each of the generations:

Selection step:

1. Calculation of the approximate objective function G for every individual.
2. Calculation of a linear interpolant $\tilde{\Delta}$ for every individual.
3. Assignment of a fitness proportional to the value $(G+\tilde{\Delta})^S$ (where s=1÷4) to every individual. Selection of NADDB~0.1·NPSIZE additional nodes among best candidates for which the accurate values of the function F are calculated.

Crossover step:

1. The probability of access to crossover proportional to the fitness value is assigned for each individual. Such a selection is usually referred to as a "roulette" method.
2. Crossover of the randomly selected pairs of individuals. Herein a standard one-point binary crossover is adopted. For this purpose first the normalized X values are transformed into a binary code and "chromosome" ribbons are formed for every individual. The ribbon length is proportional to the number of varying parameters and L being the number of bits adopted for each variable. The L is commonly equal to 4-8, that is, the range of parameters variation is divided into 2L-1=15÷255 segments. Then, the breakpoint is determined in a random manner and the ribbon portions from the "parents" are pasted together in a crossover way.
3. A portion of individuals (NELIT~0.1· NPSIZE) corresponding to the nodes which are the best at this point, find their way to the next generation without changes (elite strategy).

Mutation step:

1. The generation of "offspring" obtained as a result of the crossover is subjected to an additional mutation procedure with a small probability Pm << 1. For this purpose "1" is flipped to "0" or vice versa in some of randomly chosen cells. The mutation step is necessary to prevent the population from degeneration, that is, from the optimization process sticking in a local optimum. At initial optimization stages the probability of mutation is increased with the aim of checking the entire space for the presence of the regions with high values of the objective function. To curtail the search region the Pm is decreased as the global optimum is approached.

Overall, the hybrid GA differs little from the conventional GA. Test examples have revealed that the hybrid GA is inferior to the conventional one with the equal sizes of population NPSIZE, but has the same effectiveness for doubled population (Fig.1). In this case the number of computations using the exact model is less by a factor of five for the hybrid method, while the net gain in the computer times depends on the relative costs of the high- and low-fidelity calculations.

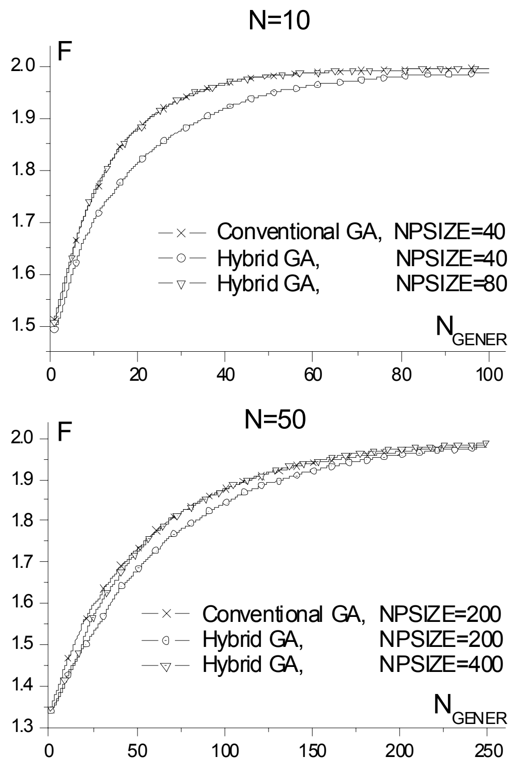


Fig. 1 Comparison of conventional and hybrid GAs

Aerodynamic design results

The first example relates to an aerodynamic configuration of an advanced short/medium-haul airplane for 120-160 passengers. The investigations on this configuration are carried out intensively at TsAGI. The aim of the aerodynamic design is to find a wing shape with good L/D-ratio over a certain velocity interval: $0.78<M<0.82$. Three different flight regimes were taken into account M=0.80 Cl=0.525; M=0.81 Cl=0.515; M=0.82 Cl=0.5, which correspond to the condition of the same lift $M^2 \bullet Cl=const$.

As a high-fidelity model the very fast domestic full-potential code BLWF is used [18]. The calculation of an external flow is carried out by numerical integration of the conservative form of the full potential equation with the approximate non-isentropic correction on shocks. The solution of resulting equation system is obtained by using an effective approximate factorization algorithm. Three-dimensional computational grid of C-H type over a wing-fuselage configuration is generated using simple algebraic technique. An inclusion of nacelles, pylons, empennage and winglets is possible on the basis of "chimera" approach (Fig. 2).

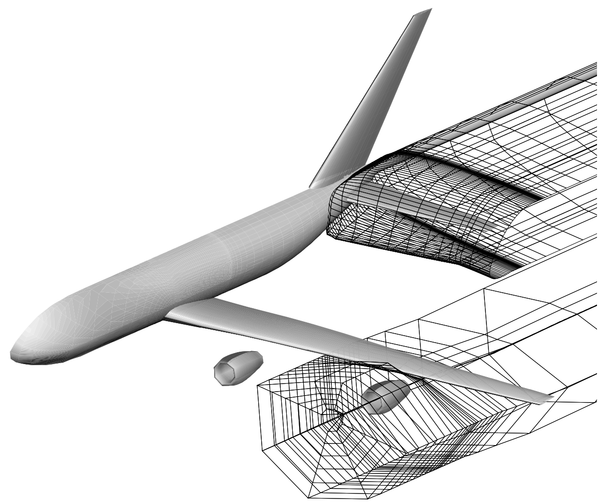


Fig.2

The calculation of a compressible laminar and turbulent boundary layer on a surface of a wing and empennage is carried out by finite-difference technique. The application of a quasi-simultaneous technique has provided fast convergence of viscous - inviscid iterations, both for attached flow and moderate separation regimes. As a rule, five iterations for the achievement of full convergence are sufficient. High speed of the code (the time of one run with nacelles taken into account is about 40 sec on PC Pentium IV-2400 on the third finest grid) provides a good basis for its application in the optimization design procedures.

As a low-fidelity model computations were used with the same code on the second mesh (run time 8 sec). Twenty-two design variables were global geometry variations (camber, twist, upper surface crest position etc) of the baseline sections along span. Multiobjective genetic algorithm (MGA) has been utilized with the population of size NPSIZE=50 allowed to evolve over 50 generations. Each objective function evaluation corresponds to 6 analysis runs, so the whole optimization process in conventional GA mode took about one week on PC Pentium IV-2400. The same task has been solved in only about 2 days using accelerated GA. Pareto-front of the design problem is shown in Fig.3. It was very informative to investigate Pareto-front for understanding trade-offs between multiple criteria and choosing appropriate compromise wing geometry.

While in the first example we have considered single aircraft, the second example relates to designing of the same wing configuration for two different aircraft: regional jet and business one with the shorten fuselage (Fig.4). Design flight regimes are (M=0.78 Cl=0.5) and (M=0.815 Cl=0.4) correspondently. Besides of varying M and Cl values, different relative position of the engine is also important factor greatly influencing flow pattern over the wing.

The design problem has been solved in two ways. Alongside with the multicriteria problem five single-criteria optimization problems were solved, each with its own weight distribution among the criteria. The computational results are shown in Fig.5. It is evident that the Pareto-front is covered non-monotonically with uniform variation of the weights, so it would be difficult to choose appropriate weights in advance. Single- and multiple criteria optimizations are well correlated. However the computational burden for MGA

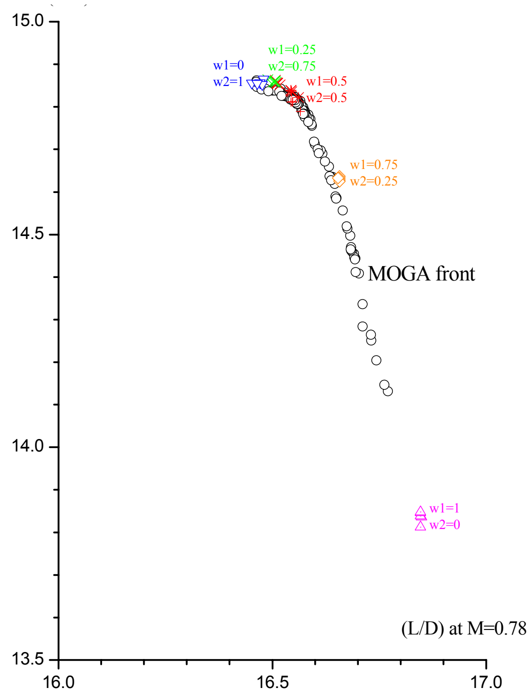


Fig.5

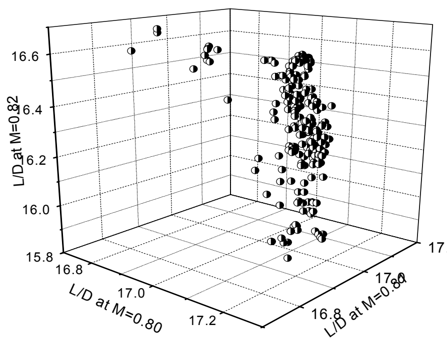
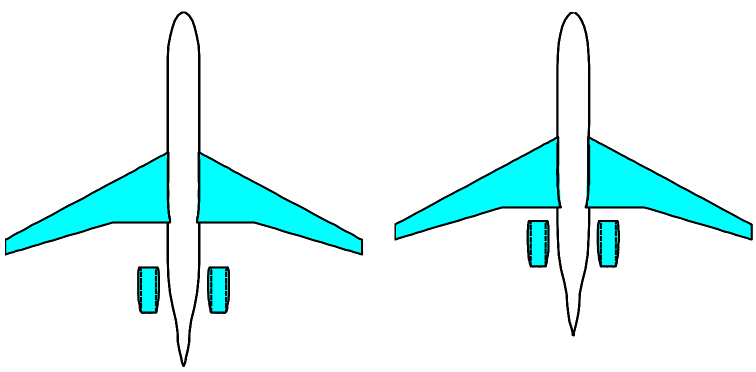


Fig.3



Regional jet;
M=0.78 Cl=0.5

Business jet;
M=0.815 Cl=0.4

Fig.4

are only 1.5 times greater than for each single-criteria optimization run. Even more benefit in the whole effectiveness of the optimization process could be obtained with increased number of criteria considered.

The third example deals with designing of the wing for an advanced high-speed long-haul airliner with cruise Mach number of 0.88. The cylindrical fuselage was considered, our previous studies have shown that the fuselage shape deformations are helpful starting with M~0.92-0.93 [19]. The following geometric parameters of the wing were chosen: sweep $\chi_{1/4}$=36°, aspect ratio λ=7.75, taper ratio η=4, thickness at the root, kink and tip t/c = 14% - 9.25% - 8.5%, respectively. Five design flight regimes were taken into account, the main complexity being connected with their appropriate choice, because of the extreme sensitivity of the flow pattern to small Cl and M changes not only towards increased values, but towards decreased values also.

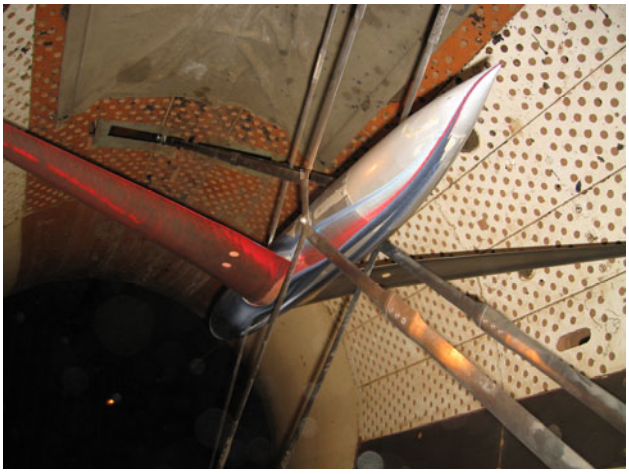


Fig.6

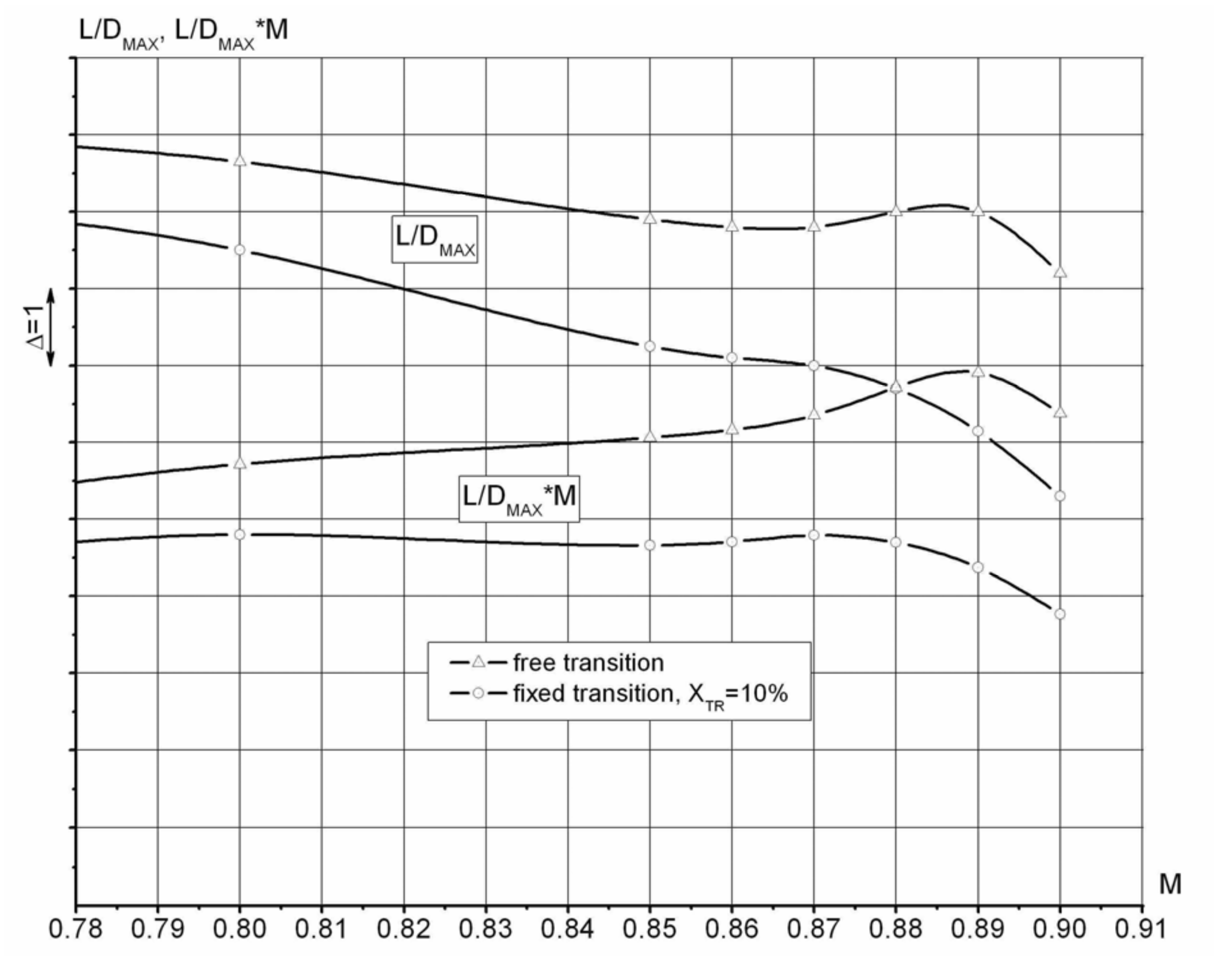


Fig.7

An aerodynamic wing+fuselage model was manufactured and Fig.6 presents this model installed in TsAGI's transonic wind tunnel T-106M. The experimental maximum lift-to-drag ratio of the configuration versus Mach number is shown in Fig.7 for free and fixed transition conditions. It is evident that good agreement with the design goals is achieved. Future studies will include rational engine accommodation and high-lift characteristics.

Conclusions

The presented examples are indicative of the applicability of the developed hybrid method to solving practical optimization problems when numerical methods of various levels of complexity are available, and particularly to aerodynamic design problems. The optimization program is structurally completely separated from the direct computation codes and can be used for other applications. Further investigations are needed for effective utilization high- and low-fidelity models in order to increase the effectiveness of the hybrid GA else.

References

[1] J.C.Vassberg, P.G.Buning, C.L.Rumsey. Drag prediction for the DLR-F4 wing/body using OVERFLOW and CFL3D on an overset mesh. AIAA-2002-0840.

[2] Michalewicz Z., Genetic algorithms + data structures = evolution programs, Springer-Verlag, Berlin, 1994.

[3] P. Hajela Nongradient methods in multidisciplinary design optimization – status and potential. J. Aircraft Vol. 36, No 1, January-February 1999.

[4] A.Vicini, D.Quagliarella. Inverse and direct airfoil design using a multiobjective genetic algorithm. AIAA Journal, vol.35, №9, 1997.

[5] Genetic algorithms for optimization in aeronautics and turbomachinery. VKI Lecture Series 2000-07.

[6] Gen M., Cheng R. Genetic algorithms & engineering design. New York, John Wiley & Sons, 1997.

[7] Torczon V., Trosset M. Using approximations to accelerate engineering design optimization. AIAA-98-4800 in 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 1998.

[8] R.Duvigneau, M.Visonneau. Hybrid genetic algorithms and neural networks for fast CFD-based design. AIAA-2002-5465 in 9th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 2002.

[9] Giannakoglou K. Coupling evolutionary algorithms, surrogate models and adjoint methods in inverse design and optimization problems, in VKI Lecture Series 2004-07.

[10] Alexandrov N., Lewis R., Gumbert C., Green L. Newman P. Approximation and model management in aerodynamic optimization with variable fidelity models. J. Aircraft, vol. 38, №6, 2001.

[11] S.Tursi. Transonic wing optimization combining genetic algorithms and neural networks. AIAA-2003-3787.

[12] A.Le Moigne, N.Qin. Variable-fidelity aerodynamic optimization for turbulent flows using a discrete adjoint formulation. AIAA Journal, vol.42, №7, 2004.

[13] I.L.Chernyshev. Hybrid two-level genetic optimization algorithm with different fidelity models for aerodynamic design problems. ICAS Congress 2002, Toronto.

[14] Simpson T.W., Replinski J., Koch P.N., Allen J.K. Metamodels for computer-based engineering design: survey and recommendations. Engineering with Computers, vol.17, №2, 2001.

[15] N.V.Queipo, R.T.Haftka, W.Shyy, T.Goel, R.Vaidyanathan, P.K. Tucker. Surrogate-based analysis and optimization. Progress in Aerospace Sciences, v.41, №1, 2005.

[16] D.L.Knil, A.A.Giunta, C.A.Baker, B.Grossman, W.H.Mason, R.T.Haftka, L.T.Watson. Response surface models combining linear and Euler aerodynamics for supersonic transport design. J.Aircraft, vol.36, №1, 1999.

[17] A.J.Keane. Wing optimization using design of experiment, response surfaces and data fusion methods. J.Aircraft, vol. 40, №4, 2003.

[18] A.L. Bolsunovsky, N.P. Buzoverya, Karas O.V., Kovalev V.E. Advances in aerodynamic design methods for subsonic aircraft cruise configuration. 43-rd Israel annual conference on aerospace sciences, Tel Aviv-Haifa, 2003.

[19] A.L. Bolsunovsky, N.P. Buzoverya. Transonic wing design using inverse and optimization methods. Journal of Advanced Engineering Design, vol.40, №1, 2000.